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WIRELESS INDOOR LOCALIZATION USING PATHLOSS-BASED TECHNIQUES

Master of Science thesis

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ABSTRACT

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Location based services (LBS) have become very popular in recent years. LBS use location data to provide different features to the user, such as entertainment, security, emergency services, tracking and real-time information. At present time, the Global Positioning System (GPS) is the most popular and reliable solution in the commercial navigation market, but it is used mainly for outdoor areas. Consequently, different lines of investigation have been open, aiming to create alternatives which solve the localization problem for indoor areas. One of these lines of research focuses on using wireless networks as the technology capable to overcome the challenges presented by GPS systems in indoor environments.

In this thesis, we have implemented a real indoor positioning solution based on pathloss models using wireless LAN networks. It performs localization at its finest under the worst conditions. For that purpose, three different WLAN indoor localization techniques have been developed for Android-based mobile devices: AP-Identification (AP-ID), Pathloss-based method using trilateration and Pathloss-based method using Extended Kalman Filters (EKF). The performance of such algorithms is evaluated in terms of Root Mean Square Error (RMSE).

PREFACE

I would like to express my gratitude to my supervisor and examiner Professor Jari Nurmi, for all the support offered since the beginning of this MSc thesis. Specially, I would like to thank to my supervisor Francescantonio Della Rosa, for his constant feedback and useful advice, for guiding me through the learning process of this master thesis and for giving me the great opportunity to carry out this project.

Finally, I acknowledge my parents, who have been always supporting me since the first day, helping me in every decision taken. Last note goes for my friends, who have become a new family for me. Thank you.

Tampere, 31 October 2015

Raul Serna Marin

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LIST OF ABBREVIATIONS

AOA	Angle of Arrival
AP	Access Point
AP-ID	Access Point Identification
API	Application Program Interface
BS	Base Station
BSSID	Basic Service Set Identifier
Cell-ID	Cell-Identification
DB	Database
DSSS	Direct-Sequence Spread Spectrum
EJML	Efficient Java Matrix Library
EKF	Extended Kalman Filter
FHSS	Frequency-Hopping Spread Spectrum
GPS	Global Positioning System
IEEE	Institute of Electrical and Electronics Engineers
KF	Kalman Filter
LOS	Line Of Sight
LS	Least Squares
LLS	Linear Least Squares
MAC	Medium Access Control
MAN	Metropolitan Area Network
MVC	Model-View-Controller
MIMO	Multiple-Input Multiple-Output
MS	Mobile Station
NLLS	Non Linear Least Squares
NLOS	Non Line Of Sight
NN	Nearest Neighbor
OFDM	Orthogonal Frequency Division Multiplexing
OSI	Open Systems Interconnection
PAN	Personal Area Network
PHY	Physical Layer
PL	Pathloss
RMSE	Root Mean Square Error
RFID	Radio Frequency IDentification
RSS	Received Signal Strength
SDK	Software Development Kit
SSID	Service Set Identifier

TDOA	Time Difference Of Arrival
TOA	Time Of Arrival
TUT	Tampere University of Technology
WAN	Wide Area Network
Wi-Fi	Wireless Fidelity
WiMAX	Worldwide Interoperability for Microwave Access
WLAN	Wireless Local Area Network
WLLS	Weighted Linear Least Squares
WMAN	Wireless Metropolitan Area Network

1. INTRODUCTION

Today, we live in a new technology era, where mobile devices provide a wide range of services. Seamless connectivity, portability and accessibility are essential for the mobile user [46], which attempts to access the information resources at any time, in any place.

In the past, mobile phones were typically used for voice calls and SMSs, whereas in the present, the so-called *smartphones* aim for a large variety of services: providing social interaction through social network applications, mobile banking and payments using different technologies, remote control of several devices, etc. In other words, mobile phones have become an indispensable tool for the human being. As a consequence, a large growth in research and technical development activities is nowadays occurring in order to improve the current mobile phone engines [12].

Location based services (LBS) have become very popular in recent years. LBS use location data to provide different features to the user, such as entertainment, security, emergency services, tracking and real-time information. Providing reliable localization is one of the cornerstones of LBS. Therefore, there is lately a growing interest on developing accurate and efficient positioning and tracking systems [51].

At present time, the Global Positioning System (GPS) is the most popular and reliable solution in the commercial navigation market, providing a wireless and autonomous technology with relatively high accurate localization and global coverage. However, there are several shortcomings on GPS that can not be ignored. First, when a GPS is embedded on the mobile device, it leads to increased size, cost and battery consumption [43]. Furthermore, the reliability of GPS degrades in urban areas and indoor scenarios, where it occasionally occurs that mobile device is not on line of sight with four or more satellites, losing its track. Moreover, caused by the several obstacles in these environments, signals frequently become too weak due to interference and high attenuation [43]. As a consequence, GPS can not be used for urban and indoor positioning.

Nowadays, there exist a large number of additional methods for outdoor environments, which provide relatively accurate solutions and overcome most of GPS drawbacks. However, there is still a lack of accuracy on indoor localization systems, resulting in navigation companies putting their effort and interests on indoor position technologies. Consequently, different lines of investigation have been open, aiming to create alternatives which solve the localization problem for indoor areas.

1.1 Signals of Opportunity in Indoor Positioning

One of these innovative areas is based on using Signals of Opportunity (SoO), signals which are not intended for navigation but for communication purposes, being originated from the wireless backbone that is already in place. Therefore, there is no need of building any extra infrastructure or adding new hardware to mobile devices. Moreover, SoO overcome main GPS challenge: they are able to reach the areas where GPS is unable to work, such as urban outdoors and inside buildings, by using the technology which is already set up in the environments [26].

There are several short range RF technologies such as RFID, Bluetooth or WLAN, which use signals of opportunity for locating mobile users in indoor environments.

RFID (Radio Frequency IDentification) is a tracking technology which uses electronic tags to identify people or objects. It does not require line of sight between the reader and tag, hence performing well in crowded indoor scenarios. There are several lines of investigation which use RFID technology as positioning methods, since user is able to retrieve the ID and other information from different tags and perform localization. However, it requires to utilize RFID readers and tags, adding unnecessary hardware to the positioning system.

Bluetooth is a wireless communication technology for transferring information over short distances. Bluetooth chips are embedded on many latest devices, therefore not requiring external hardware or infrastructure for its use. Moreover, Bluetooth provides high security levels within personal area networks. Bluetooth has also been widely adopted for indoor positioning purposes [13].

Wireless Local Area Network is a technology which provides wireless communication using radio signals over short distances. It is based on the IEEE 802.11 standard [1]. Main advantage with respect to Bluetooth technology is its huge widespread distribution nowadays, since WLAN technology has already been deployed on many indoor environments. As a consequence, WLAN has been the chosen technology in this MSc thesis, exploiting the Received Signal Strength (RSS) measurements for performing localization.

1.2 Goals

The purpose of this project is to study and implement a real indoor positioning solution based on pathloss models using WLAN networks. The practical application must perform localization at its finest under the worst conditions, meaning that it must always provide a positioning solution even when unfavorable circumstances occur.

The following points summarize the several goals of this MSc thesis:

- To study and analyze 802.11 WLAN technology.
- To study and analyze the RSS measurements and their challenges in indoor positioning.
- To study and analyze pathloss modeling as well as to implement empirical pathloss models on indoor environments.
- To study, propose, implement and test several indoor positioning algorithms based on WLAN networks (experiments will be conducted in a university building in the city of Tampere).

1.3 Outline

This MSc thesis is organized as follows:

Chapter 2 describes the theoretical background necessary to understand the following sections. First, wireless networking concept will be briefly described in order to present WLAN technology, which will be reviewed thoroughly. Second, fundamentals of indoor radio propagation will be introduced and phenomenons like fast fading, multipath or pathloss will be discussed.

In chapter 3, several indoor positioning approaches based on WLANs are presented. RSS-based localization approach is described in detail. Afterwards, a comparison between fingerprint and pathloss-based techniques is addressed, followed by a comparison between theoretical and empirical pathloss models, providing to the reader the different reasons why we have chosen empirical pathloss models for this MSc thesis.

Chapter 4 describes exhaustively and theoretically the actual algorithms proposed to perform pathloss-based localization on WLANs.

Chapter 5 addresses the experimental activity conducted in this work. Scenario and devices used are firstly introduced. Then, the software framework implemented is briefly explained. Finally, the three indoor positioning approaches proposed in this MSc thesis are described in detail.

Chapter 6 shows the experimental results obtained from the indoor positioning application developed by means of RMSE metric.

In Chapter 7 a discussion with the results is presented, as well as some lines of work to be addressed in a future.

2. THEORETICAL BACKGROUND

In this chapter, the theoretical knowledge for understanding indoor positioning background in local networks (WLANs) will be explained. It will be divided in two main sections:

In the first place, wireless networking topic will be briefed in order to present WLAN technology, its history over the years and its most important standard: 802.11, commercialized as Wi-Fi, which will be described exhaustively. Afterwards, section will be finished by introducing the main WLAN standards up to date.

In the second part of this chapter, fundamentals of Indoor Radio Propagation will be explained. Different topics as radio propagation, fast fading, multipath propagation, slow fading and path loss will be discussed.

2.1 Wireless Networks

Over the past fifteen years, the world has become highly mobile. As a consequence, traditional technologies have been proved insufficient for our new way of life. Instead, wireless networking has started taking the attention since it possesses no such restriction of movement, hence providing free mobility to the user and great flexibility to service providers [19].

Based on the size or range of the network, wireless networks can be classified as follows [8]:

- Wireless Personal Area Network (WPAN): With a coverage area up to 10 meters, these networks are used to transfer information over short distances, which involve little or not at all infrastructure. Such technologies are Bluetooth, ZigBee, Ultra Wide Band (UWB) and Radio Frequency Identification (RFID).
- Wireless Local Area Network (WLAN): With 100 meters as range, these networks provide coverage for limited areas such as schools, home and office

buildings. Most local network technologies are based on 802.11 standard, trademarked as Wi-Fi.

- Wireless Metropolitan Area Network (WMAN) transmits data over large distances (about 5-10 km). WiMAX technology, which belongs to 802.16 standard, together with WiBRO technology, launched in Korea, form WMAN [42].
- Wireless Wide Area Network (WWAN): It provides greater mobility due to its high coverage with ranges up to 15 - 50 Km. Technology is called Mobile Broadband Wireless Access (MBWA) and it is developed under standard 802.20.

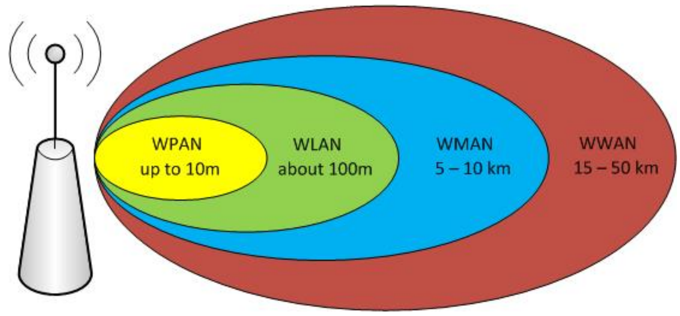

Figure 2.1 *Classification of Wireless Networks [42]*

2.1.1 Wireless Local Area Network (WLAN)

As explained in chapter 1, indoor positioning experiments have been performed within WLAN networks. Therefore, this subsection explains thoroughly the different characteristics of WLAN technology.

A WLAN is a network which provides communication to different devices (computers, mobile phones, servers, printers, etc) without having to be physically connected to each other within limited geographic areas.

First WLAN standard was originated in 1997 by the Institute of Electrical and Electronics Engineers (IEEE), and was called 802.11. Since its creation, several international organizations have developed a broad activity in the standardization of WLAN standard and they have generated a wide range of new standards [12].

Two years later, in 1999, emerges a non-profit organization called *Wireless-Fidelity (Wi-Fi) Alliance*, whose main purpose is to certify interoperability among IEEE 802.11 network equipment, and also, promote the standard. Wi-Fi Alliance owns the *Wi-Fi Certification* trademark, which is only allowed to those devices which conform their specifications. Meeting their requirements permits an interoperability between different equipment from different vendors, and also compatibility between new and old Wi-Fi products.

Wi-Fi products are identified as 802.11, and are then further identified by a lower case letter that specifies which technology is in operation, such as 802.11a. Each certification set is defined by a set of features that relate to performance, frequency and bandwidth. Each generation also furthers security enhancements and may include other features that manufacturers may decide to implement [12].

In the following lines, a brief history about WLAN's evolution is presented [6]:

- First generation (1G), IEEE 802.11. At this early stage, networks provided basic connection. There were no standards at the moment so vendors used their own system devices. Features as roaming, management and security were absent.
- Second generation (2G), IEEE 802.11b. With the creation of Wi-Fi Alliance, a global standardization emerges. Basic features such as AP management and security are developed. Hence, APs start becoming standalone AP, being able to work independently. However, when multiple APs are in the same network, there is no multiple management.
- Third generation (3G), IEEE 802.11a/g. Demands from second generation are met and centralization is developed, which allows the control of multiple APs in large networks. As this allows larger network deployments, it also brings the need of having a better coverage, connectivity and reliability among these great areas.
- Fourth generation (4G), IEEE 802.11n. Meeting 3G requirements, this new generation brings a very high throughput as well, providing high rates at large distances. Moreover, it controls effectively how radio frequency resources are used. Last but not least important, it uses robust technologies such as *multiple-in-multiple-out (MIMO)* and *space time coding*.

There is a wide variety of WLAN standards. This work focuses on 802.11b/a/g/n because they actually describe the most encountered specifications among Wireless Local Area Networks.

2.2 IEEE 802.11

802.11 is a member of the IEEE 802 family, which is a set of specifications for local WLAN technologies. Relationship between components of IEEE 802 family and their place in the *Open Systems Interconnection* (OSI) model can be seen in Fig. 2.2

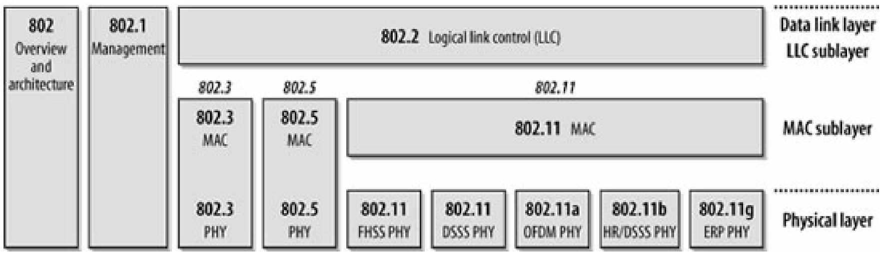

Figure 2.2 *IEEE 802 family in OSI model [19]*

IEEE 802 specifications are focused on the two lowest layers of the OSI model because they incorporate both physical and data link components. All 802 networks have both a *Media Access Control* (MAC) and a *Physical* (PHY) component. The MAC is a set of rules to determine how to access the medium and send data, whereas the details of transmission and reception are left to the PHY component [19].

802.11 is a link layer that can use the 802.2 Logical Link Control (LLC) encapsulation. At the beginning, the base of 802.11 specification included the 802.11 MAC and two physical layers: a *frequency-hopping spread-spectrum* (FHSS) physical layer and a *direct-sequence spread-spectrum* (DSSS) link layer. However, later revisions to 802.11 added additional physical layers, such as 802.11b and 802.11a. 802.11b specifies a high-rate DSSS layer (HR-DSSS), meanwhile 802.11a describes a physical layer based on *orthogonal frequency division multiplexing (OFDM)* [19]. These modulation schemes will be presented in the following lines briefly since the reader just needs to understand the basics.

2.2.1 Spread spectrum techniques

The radio physical (PHY) layers in IEEE 802.11 use different spread spectrum schemes [20]:

Frequency Hopping Spread Spectrum (FHSS)

Frequency hopping is a modulation technique where radio signal is transmitted by rapidly jumping over different carriers, following a pseudo-random pattern, which is known by the transmitter and receiver. Therefore, a non-authorized receiver would hear just unintelligible interference. These signals are highly robust against interference and noise, being also really difficult to intercept. However, its transfer rates are low compared to DSSS rates.

Direct Sequence Spread Spectrum (DSSS)

DSSS is a codification technique which spreads the power out over a wider frequency band using mathematical coding functions (pseudo-noise codes). Result signal is quite similar to noise, hence only the intended receiver will be able to distinguish the signal from noise. Among the advantages, this modulation technique allows higher data rates and requires less transmission power to achieve a reliable communication. However, it does not provide so high tolerance of signal interference as FHSS does.

Orthogonal Frequency Division Multiplexing (OFDM)

OFDM is a modulation scheme that divides a high-speed serial information signal into multiple lower-speed *subcarriers* that the system transmits simultaneously at different frequencies in parallel. The ability of separate efficiently the subcarriers lies on a mathematical concept called *orthogonality*. Subcarriers are chosen orthogonal to each other, which means that whereas a subcarrier has a maximum peak, the other ones signals are at zero point (See Fig. 2.3). OFDM provides high spectral efficiency, considerably high data rates and great tolerance to distortion.

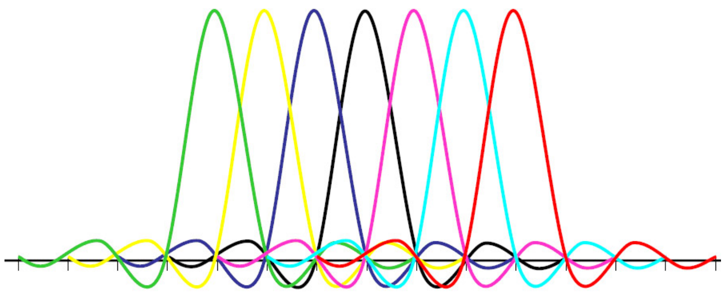

Figure 2.3 *OFDM Subcarriers [11]*

2.2.2 Physical components

802.11 networks consist of four main physical components, as they can be observed in Fig. 2.4:[19]

- Distribution system: It is the backbone network used to forward frames to their destinations.
- Access Points (AP): Used as a bridge between the wired backbone distribution system and the wireless network.
- Wireless medium: non-wired medium which moves frames from station to station.
- Mobile Stations (MS): computing devices with wireless network interfaces.

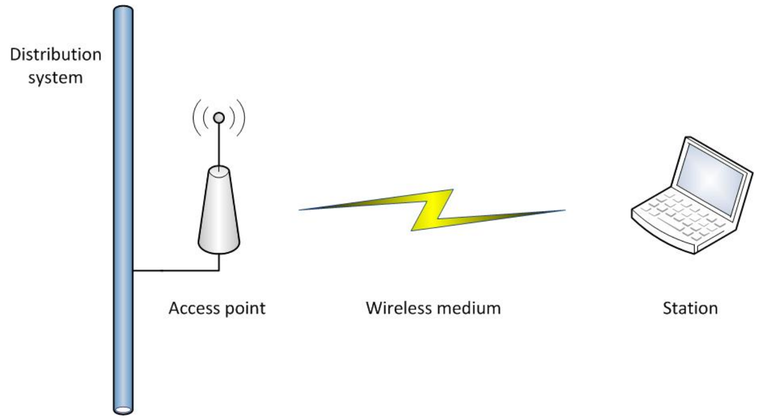

Figure 2.4 *Physical components of 802.11 networks [19]*

2.2.3 Network modes

The basic block of 802.11 networks is called *Basic Service Set (BSS)*, which is a set of stations that communicate with each other. There are two operational modes defined in 802.11 standard, *ad-hoc mode* and *infrastructure mode* (see below figure) [19]:

- Ad-hoc mode: also known as *Independent BSS*, where different stations communicate directly between them without the need of other components. They must be within a limited range. It is formed by a small number of stations which communicate over a short period of time.
- Infrastructure mode: also known as *Infrastructure BSS*, where different mobile nodes communicate through an access point (AP). If one mobile station in an infrastructure BSS needs to reach another MS, the communication process must take two hops. First, the source MS sends the data to the access point. Second, the access point forwards it to the destination station. In order to start transferring data, mobile devices must join the network, which means that they must *associate* with the access point.

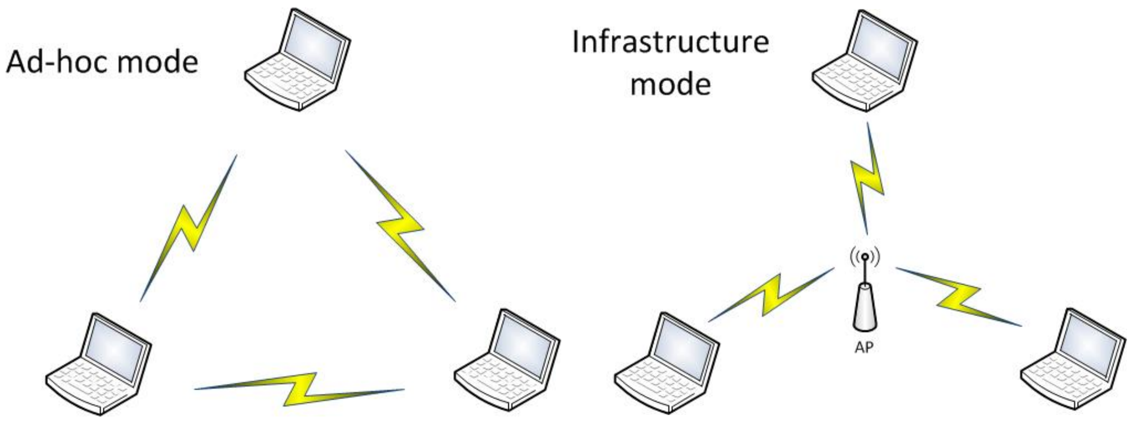

Figure 2.5 *Ad-hoc and infrastructure network mode [19]*

The BSS network modes above allow to coverage small offices and homes. However, in order to provide coverage for larger areas, it is necessary a bigger building block, called *Extended Service Set (ESS)*. An ESS is created by chaining BSSs together with a backbone network. ESSs are the highest level of abstraction supported by 802.11. In Fig. 2.6, the ESS is the union of four BSSs, and stations within the same ESS can communicate with each other, even if they do not belong to the same BSS [19].

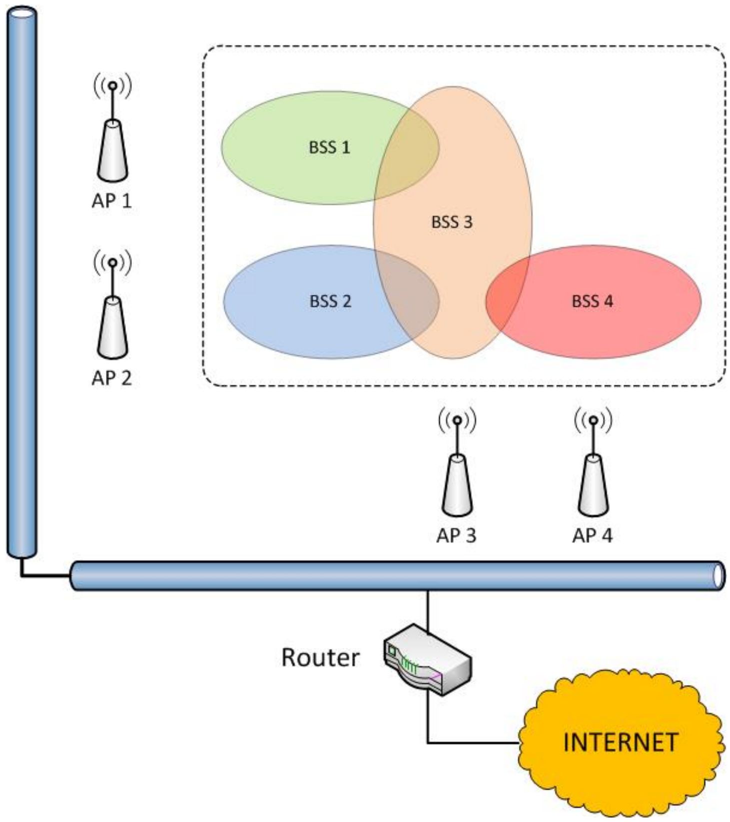

Figure 2.6 *Extended service set formed by four BSSs [19]*

2.2.4 IEEE 802.11 Standards

To conclude this section, selected 802.11 standards are presented below:

802.11b

802.11b specification was created in 1999 by IEEE trying to improve 802.11 weaknesses. It works in 2.4 GHz frequency band, uses DHSS as modulation technique and it provides a maximum transmission speed up to 11 Mbps.

802.11a

Also approved in 1999, this standard supports throughput up to 54 Mbit/s, operates at 5 GHz frequency range and uses OFDM modulation. Because 802.11b and 802.11a operate in different frequency bands, they are incompatible.

802.11g

In order to combine best of both 802.11b and 802.11a, 802.11g is created in 2003. It uses same frequency band as 802.11b, 2.4 GHz, and supports theoretical transmission rates up to 54 Mbps. It is compatible with 802.11b standard, but practical transmission speed is unfortunately affected by some degradation.

802.11n

In 2009, 802.11n specification was designed to improve 802.11g standard by using a new technology called *multiple-in multiple-out (MIMO)*. MIMO technique allows to use different channels to send and receive data by adding new antennas to the system. This results in a theoretical net data rate up to 600 Mbit/s.

2.3 Fundamentals of Indoor Radio Propagation

Experiments of this MSc thesis have been conducted in an indoor scenario, hence fundamentals of indoor radio propagation are presented. Performance of the different position techniques depends heavily on the characteristics of the radio channel. Therefore, main requirement is trying to predict the wireless channel.

In order to make an efficient channel model estimation, it is required to know how signal power decreases as it propagates through space. This signal attenuation is called *pathloss* and it is essential to characterize wireless channel correctly. Moreover, when signal travels along the path, it also experiences random variances in amplitude and phase over time, making the right prediction of the channel even more difficult. This impairment is known as *fading.* In wireless systems, fading may either be due to *fast fading* or *slow fading.*

This section will include main concepts needed to characterize a wireless channel. Firstly, *fast fading* and *slow fading* will be explained, together with their causes and effects. Secondly, term *indoor pathloss* will be introduced.

2.3.1 Fast fading

Main problem for indoor propagation environments is a phenomenon called *fast fading*, or what is the same, fast fluctuations of the received signal that vary significantly over short distances, hence adding unpredictable and potentially catastrophic effects to the wireless channel. There exist two reasons which cause it: *multipath propagation* and *Doppler shift.*

Multipath Propagation

Multipath propagation occurs when transmitted signal experiences many signal transformations along the path, arriving to the receiver as an unpredictable set of waves with different attenuation, delays and angles of arrival. This process is illustrated in Fig. 2.7.

Signal is divided in different replicas among the path due to *reflection*, *scattering* and *diffraction*, the basic radio propagation mechanisms [47]:

- Reflection. It occurs when an incident signal beam strikes a flat or smooth boundary with some incidence angle and most of the ray is reflected in some direction with a reflection angle. See Fig. 2.8
- Scattering. It is a propagation mechanism which occurs when incident wave hits a irregular or rough terrain and the wave is randomly reflected in many directions simultaneously, with much lower amplitude. See Fig. 2.9

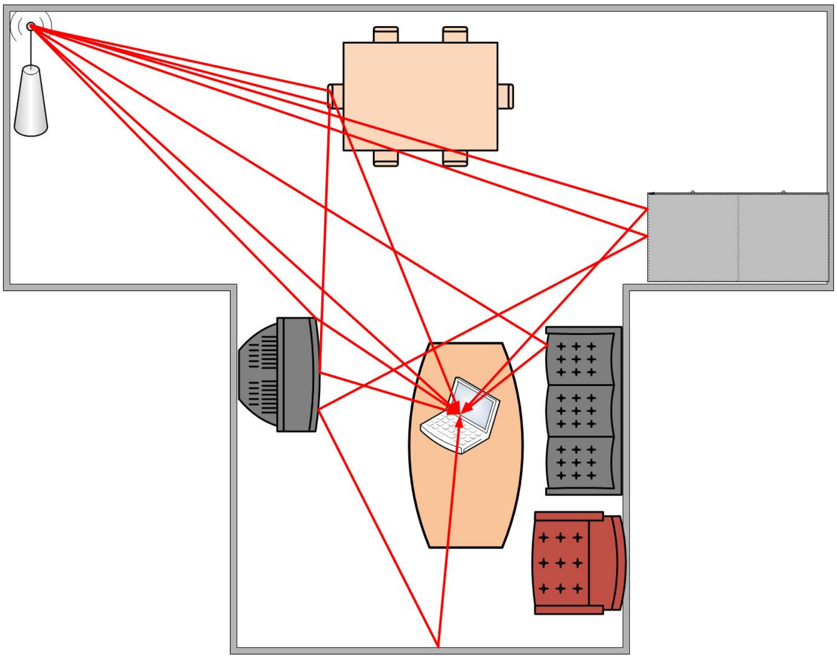

Figure 2.7 *Multipath propagation in indoors*

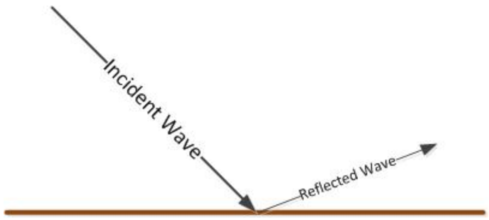

Figure 2.8 *Signal Reflection*

- Diffraction. Another propagation mechanism which occurs when a wave goes around/over an obstacle. How waves spread over is based on Huygens's principle [29]. See Fig. 2.10

Doppler shift

The *Doppler effect* (or *Doppler shift*) is the frequency change produced by the relative motion of the source to its observer (see Fig. 2.11). The maximum Doppler frequency is given by equation $f_{dmax} = \frac{v}{\lambda}$, where v is the speed of source towards the static observer and λ is the wavelength of the signal. If the mobile device is moving towards to the source, frequency increases. If the mobile device is going away, Doppler frequency decreases. It results in random frequency changes on the transmitted signal due to different Doppler shifts on each of the multipath components, leading to signal fading [38].

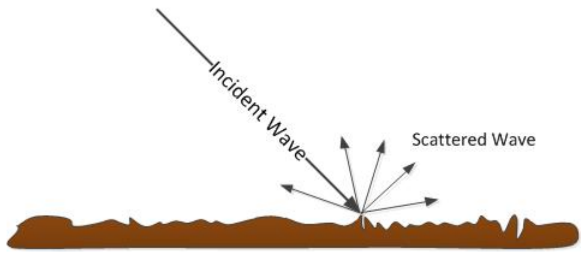

Figure 2.9 *Signal Scattering*

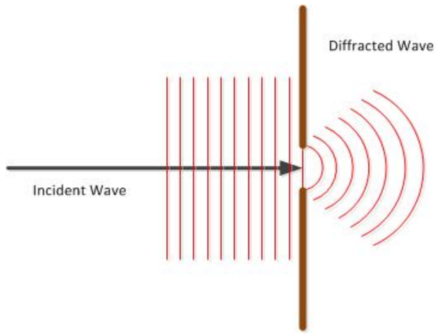

Figure 2.10 *Signal Diffraction*

2.3.2 Slow fading

Also known as *shadowing*, it is the variation of the local mean signal over a wide area. It occurs when the signal level is affected by large obstacles over long distances along signal path. Shadowing effect is less significant in indoor environments, where signal paths are not often within large distances [44].

2.3.3 Pathloss

Pathloss is the attenuation that signal suffers when it propagates through space. One of the major requirements in wireless networks is calculating this pathloss for defining accurately the distance between transmitter and receiver. However, in practical cases, due to the lack of predictability in wireless communications, pathloss calculation is done by a series of approximations. This process is called *pathloss estimation*.

Over the years, different pathloss models have been developed. There are several available choices depending on the environment requirements. Pathloss models are classified into three categories [10]:

- *Theoretical models*: models which treat analytically certain propagation mechanisms. They need a huge amount of precise information about the environment and require significant computation time. Therefore, these models are

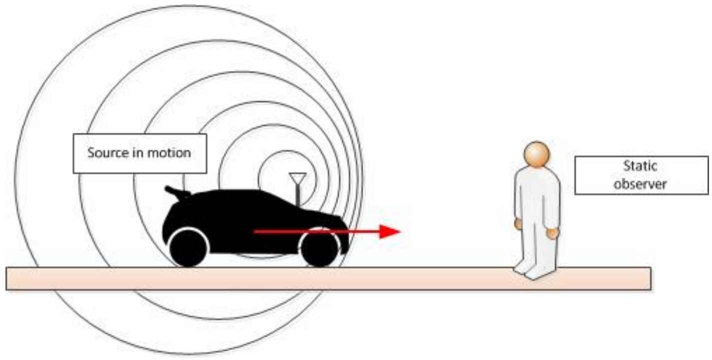

Figure 2.11 *Doppler effect*

potentially accurate.

- *Empirical models*: they are typically equations derived from massive field measurements using regression methods. They are simple to predict and provide low computational effort but there exists a lack of accuracy.

- *Semi-empirical models*: theoretical models which introduce certain empirical corrections.

In contrast to outdoor scenarios, indoor pathloss is very difficult to estimate since attenuation is highly unpredictable due to many objects (static and moving), walls and ceilings obstructing the path. Moreover, each scenario has its own characteristics which make indoor estimation site-specific.

In this work, empirical pathloss model has been chosen for our purposes, as we will see in more detail in section 3.3.5.

3. INDOOR POSITIONING METHODS BASED ON WLAN

In this chapter, a collection of positioning techniques based on WLAN networks is shown.

The target of indoor positioning methods is to locate a MS inside of a closed structure, such as a shopping mall, an airport or a hospital. For that purpose, localization methods rely on a set of anchor points distributed within the scenario.

In this MSc thesis, positioning algorithms are based on WLAN networks, available in most of indoor areas. Accordingly, APs behave as the reference/anchor points and MS as the nodes to be located. As a consequence, position of MS is estimated by the own MS device using the information received from the visible APs. Accuracy of the algorithms depends on the density of these reference points in the indoor location as well as the indoor channel conditions [41], described in section 2.3.

There are many possible classifications in literature for indoor localization techniques [18][7][49]. One of the most common classifications and the one selected for this work categorizes positioning techniques based on the type of information that is obtained from the APs. There are three main metrics which a MS can obtain from an AP: time, angle and received signal strength. It results on the next classification:

- Time based methods:
  - *Time of Arrival (ToA)*
  - *Time Difference of Arrival (TDoA)*
- Angle based methods: *Angle of Arrival (AoA)*
- Received signal strength based methods:
  - *Cell-Identification (Cell-Id)*
  - *Fingerprint*
  - *Pathloss-based*

3.1 Time based localization

The reception time of the signal transmitted by the base station is the metric measured at the mobile station, and the key to estimate user position. It defines the propagation time of the signal.

3.1.1 Time of Arrival

By using this *time-of-arrival*, distance between source and receiver can be calculated by applying a linear relationship with the *signal speed*, denoted as c:

$$distance = ToA * c$$

Once distances between MS and several reference points have been measured, mobile station position is computed as the intersection of three or more circles with *radii* the computed distance and centers the known anchor point positions. This technique is known as *trilateration* and it is illustrated in Fig. 3.1.

Small errors measuring metric *time-of-arrival* between base stations and MS will cause large errors in the computed distance, since it is multiplied by signal speed. Therefore, the several anchor points must be perfectly synchronized. However, synchronization requirement is hard to be fulfilled in WLAN scenarios and, consequently, this technique is rarely addressed in WLAN based positioning [12]. Since measurements are obtained at receiver, mobile station must be also synchronized with base stations, for which it needs additional hardware.

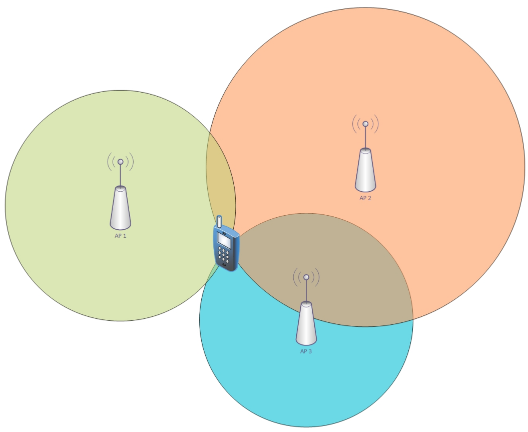

Figure 3.1 *Time of Arrival technique*

3.1.2 Time Difference of Arrival

The metric measured in this technique is the difference in arrival times between two anchor points at the mobile station. Geometrically, *TDoA* between two base stations defines an hyperbola line where mobile station is located. As a consequence, two or more hyperbolas created by three or more BSs will intersect on MS location, estimating its final position. (see Fig. 3.2)

In comparison with ToA technique, there is no synchronization requirement between anchor points and mobile stations but it is still necessary for different anchor points to be synchronized [14].

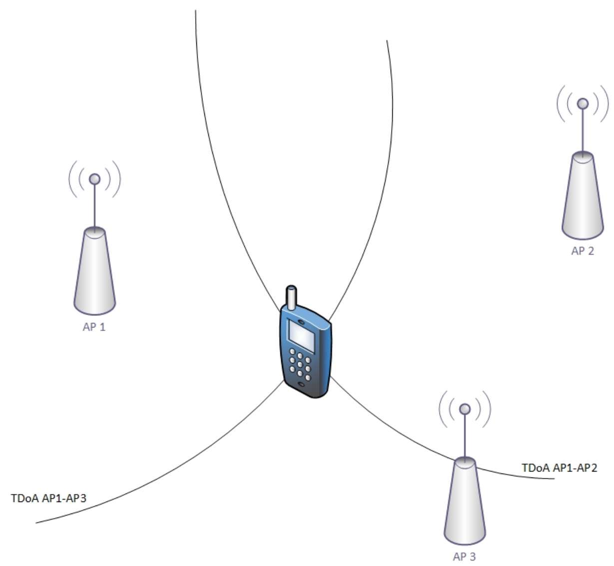

Figure 3.2 *Time Difference of Arrival technique*

3.2 Angle based localization

Angle of Arrival from mobile station is measured at the base station. Position of the MS can be found as the intersection of at least two lines, which means that this technique requires at least two base stations for computing estimations (see Fig. 3.3).

Drawbacks of this technique are that base stations must utilize multi-array antennas and accuracy is severely degraded with *Non-Line-Of-Sight* (NLOS) conditions.

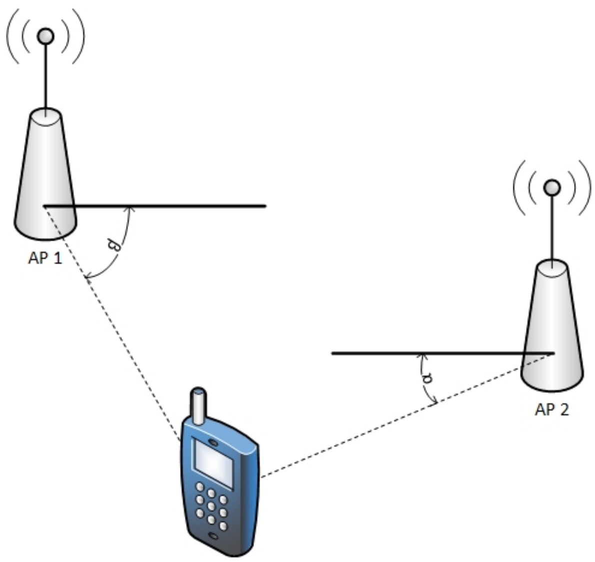

Figure 3.3 *Angle of Arrival technique*

3.3 Received Signal Strength based localization

RSS-based positioning uses the received power at the mobile station, called *Received Signal Strength (RSS)*, to estimate distance between the source (AP) and the receiver (MS). Therefore, the MS location is estimated using models that relate the strength of the received radio signal either to the distance between the MS and the signal emitter or to the MS location directly [14].

RSS measurements are considered to be more available than ToA or AoA observables since RSS values can be listened passively in a wireless network, with no need of adding extra traffic to the WLAN links[14]. Moreover, they provide better accuracy on WLANs than previous techniques. These are the reasons why we have approached RSS-based techniques in this work.

In the following lines, a brief explanation about how the mobile station reads the RSS levels from the APs is presented.

As IEEE 802.11 standard specifies [1], each Access Point periodically multicasts beacon frames which contain management information, network identification parameters, synchronization data and other control frames. MS scans the different wireless channels and buffers the data from the beacons, computing the received power at its side. Consequently, after every MS sweep, it obtains the received signal strength (among other information such as MAC address or timestamps) of all APs visible for the MS. This process is illustrated in Fig. 3.4.

In general, the beacon interval is set to 100ms, which provides good performance

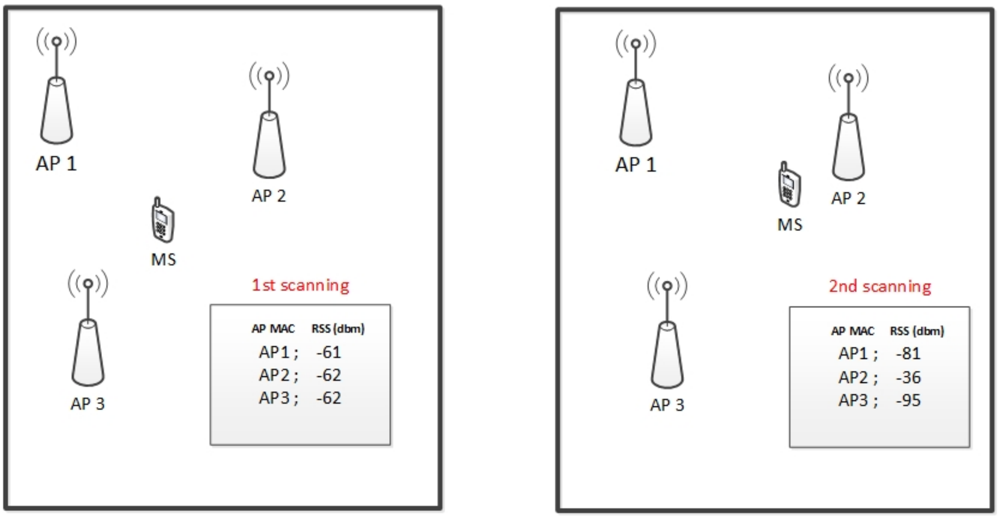

Figure *3.4 Basic example of Wi-Fi scanning process*

for most applications [21]. However, it will depend entirely on the specific network, since this parameter can be modified at the WLAN interface. Beacon intervals differ from *client listen interval*, which is the period of time at which MS decides to sweep the network channels. It must be determined before performing localization and will take into consideration different factors:

- It must be longer than beacon interval as otherwise MS will buffer repeatedly same data from the available APs. As mentioned before, beacon intervals are set by default to *100*ms. There are 12 frequency channels so client scanning interval should be longer than $100ms * 12 = 1.2s$ in order to make sure that MS is able to scan all the available APs.
- It must be longer than the time that takes MS to estimate its own position.
- It cannot be long period of time since low latency applications as positioning techniques require fast repetition rates.

Therefore, this parameter will be experimentally determined based on the scenario conditions and techniques used.

RSS-based positioning methods can be divided into three main categories, depending on how MS position is estimated from RSS measurements: cell identifier based, fingerprint and pathloss-based.

3.3.1 Cell-Identifier

Cell-Identifier based method, also called *Cell-id*, is a proximity technique where MS position estimate is stated as the position of the relative anchor point with strongest received power. Its name comes from the fact that a network is divided into several cells, each with its own base station at the center. Consequently, position of the terminal will be deduced from the cell it is connected to.

In WLAN positioning, this technique is actually called *AP-Id* technique since anchor points are APs instead of BSs. Exact location of MS remains unknown and its position is approximated by selecting the AP with strongest RSS value from all the available APs (see Fig. 3.5).

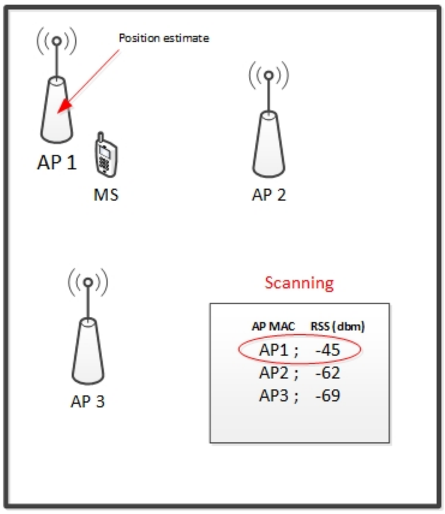

Figure 3.5 *Cell-Id based technique example under normal conditions*

Cell-ID technique works under the implicit assumption that the MS position estimate is always the AP position which is closest to it. However, in indoor scenarios there are wireless environment degradation sources such as noise, interference and fading that might affect this assumption (see Fig. 3.6).

Cell-ID method provides a low-cost positioning technique that is really easy to deploy and develop. Because of the coarse granularity of the estimate and noise introduced by the environment, this method is suitable only in scenarios where approximate solutions are enough [14].

3.3.2 Fingerprint

Fingerprint techniques estimate user position by comparing the real-time captured data with databases of fingerprints obtained before performing localization. A loca-

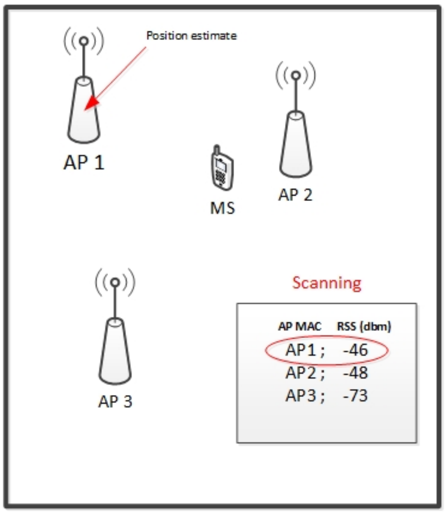

Figure 3.6 *Cell-Id based technique example under extreme conditions*

tion fingerprint is a signal information sample formed by geographical coordinates of an specific position paired with the RSS value at that location.

Compared to other RSS-based techniques, fingerprint approaches are considered to be more robust against signal propagation errors such as multipath or attenuation generated by walls and other structures; fingerprint positioning actually makes use of these location dependent error characteristics of radio signals [14]. Per contra, they suffer from a serious shortcoming: the need of building a huge fingerprint database, that is a laborious and highly time-consuming task.

Deployment of a fingerprint system consists of two main phases: offline and online phase, detailed in Fig. 3.7.

Offline phase

At the offline stage, location fingerprint database is created by performing an extensive site-survey of the received power from several APs in the area of interest. This process involves measuring the received power level of a mobile station target in several coordinates and storing the collected RSS values at each point with the corresponding location in the fingerprint database.

Online phase

At the online phase, run-time localization is achieved. For estimating MS position, new measured RSS values are related with the information stored in the fingerprint

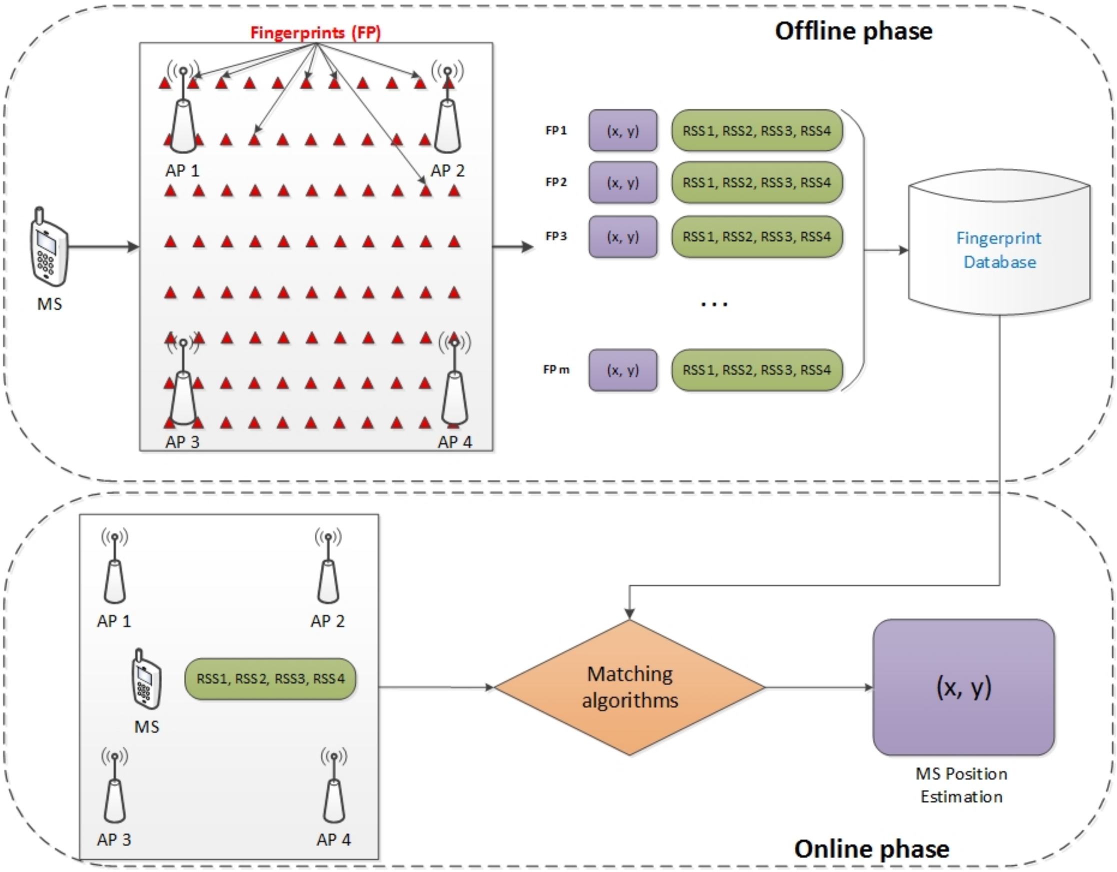

Figure 3.7 *Basic fingerprint scheme*

database via pattern matching. Mobile station scans wireless channels and captures received signal strengths from several APs, performing then a search for the fingerprint in the database with the closest match.

There are different matching algorithms in fingerprint positioning literature and can be divided in four main categories: probabilistic or Bayesian methods, k-nearest-neighbor (kNN), neural vectors and support vector machine (SVM) [52].

3.3.3 Pathloss-based

Pathloss-based localization uses pathloss propagation models to translate RSS to distances between MS and several APs. When distances are computed, several positioning algorithms can be applied to estimate the position of the MS. MS needs to capture RSS values from at least three APs in order to achieve an unique solution.

Pathloss-based methods, as fingerprint positioning, consist of two stages: calibration phase and online phase; described in Fig. 3.8 and explained in the following lines.

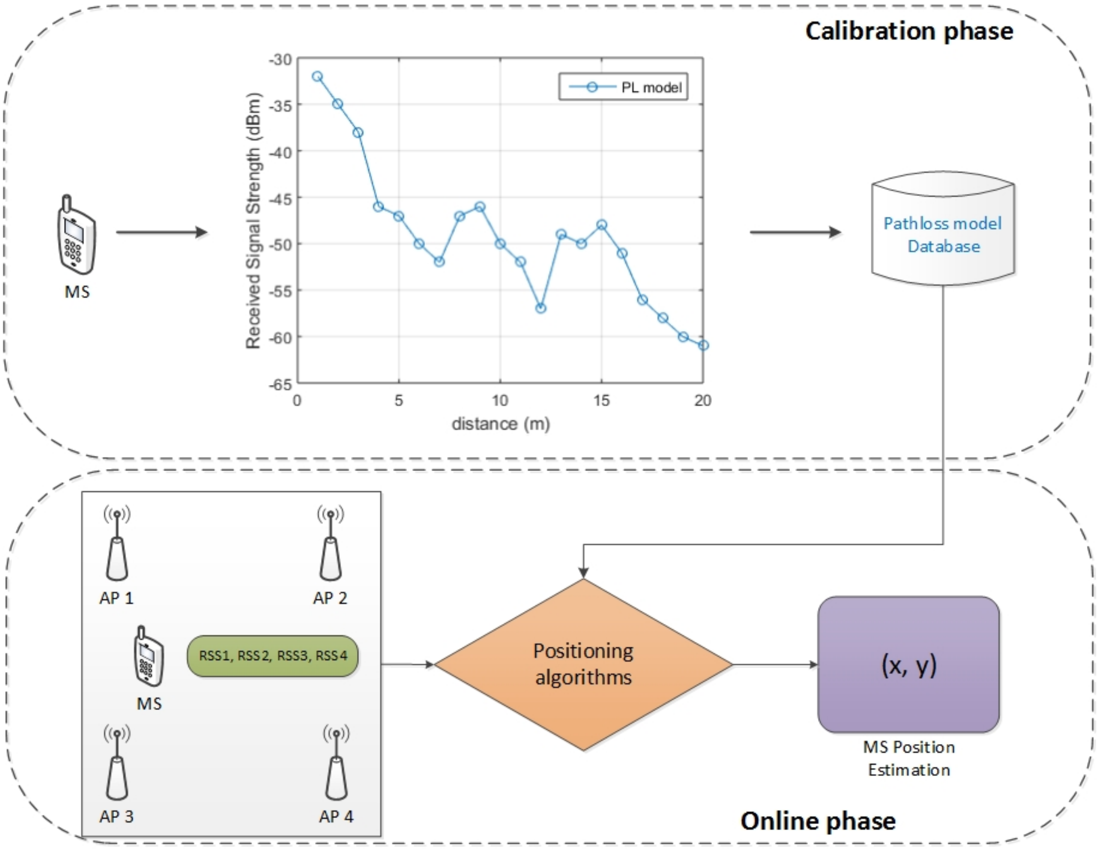

Figure 3.8 *Basic pathloss-based positioning scheme*

Calibration phase

At calibration phase, a valid propagation model is built for converting RSS measurements into distances. As it was explained in subchapter 2.3.3, a pathloss model is a mathematical expression representing the relationship between received power measurements and distance between transmitter (AP) and receiver (MS). When pathloss expression is estimated, it is stored into the device.

Online phase

At online (run-time) phase, MS position is estimated. For that purpose, RSS measurements captured from at least three APs at the receiver are translated into distances using the pathloss model stored into the mobile station. Then, location of the device can be estimated by applying localization algorithms with the estimated distances.

In this MSc thesis, two different techniques have been approached: trilateration based on *Least Squares* approximation and *Kalman* filter estimation. They are addressed in detail in chapter 4.

3.3.4 Fingerprint vs pathloss-based techniques

Due to the high fluctuations of RSS levels in indoor scenarios caused by multipath propagation, fading and attenuation, establishing an appropriate pathloss model is a very difficult task. Therefore, there is always a lack of accuracy when using pathloss-based techniques. Consequently, localization errors retrieved from PL-based techniques are commonly greater than in fingerprint approaches [14].

However, fingerprint positioning needs a large database to perform efficient localization, and its generation and maintenance are not trivial tasks. Not only building the database is a costly procedure but also it is its maintenance. Furthermore, fingerprinting does not manage well environment changes. For instance, some furniture movement or an AP being relocated will produce an inconsistency between the database and the information provided by the MS at the online stage, resulting into some accuracy lost or, ultimately, an error output [25].

Pathloss-based methods also perform a site-survey of several RSS measurements in calibration phase, generating a database which is only suitable for the indoor scenario where it was created. Nonetheless, survey requires many fewer RSS samples in order to estimate pathloss parameters. Moreover, pathloss-based techniques still perform acceptably when changes in the environment occur.

These are the reasons why we have proposed pathloss-based techniques in this MSc thesis.

3.3.5 Theoretical vs Empirical pathloss models

In this section, theoretical and empirical pathloss models will be thoroughly explained and compared.

Theoretical pathloss models

Theoretical models estimate transmission losses from analysis of the geometry of the terrain between transmitter and receiver. They are based on the fundamental principles of the phenomena of radio wave propagation. There exist different theoretical pathloss models in literature for different conditions [45][35]. The theoretical radio wave propagation model described in [32][14] shows the relationship for indoor scenarios between received power and distance, among other parameters:

$$d = 10^{(P_{tx} - P_{rx} + G_{tx} + G_{rx} - X_a + 20log(\lambda) - 20log(4\pi))/10n} \tag{3.1}$$

where d(m) is distance between Tx-Rx, P_{tx}(dBm) is transmission power, P_{rx}(dBm) is received power at mobile station and G_{tx}(dBi), G_{rx}(dBi) are the antennas gains. X_a is a Gaussian variable with standard deviation a which models the slow fading phenomenon. λ is the wavelength of the signal and n is the *pathloss exponent* between source and receiver.

As observed, there are some parameters such as X_a and, especially pathloss exponent n, which are tuned depending on the indoor conditions of the scenario. As mentioned in section 2.3, indoor scenarios are characterized by static and dynamic objects, causing fast fading and shadowing. Consequently, by only estimating these parameters, theoretical models are not reliable and accurate enough to characterize the whole indoor environment. If these conventional propagation models are used to estimate distances between the transmitter and the receiver, resulting distances will contain several errors and localization will be poorly performed. Thus, it becomes crucial to find pathloss models which fit the target environment [14][37][34].

Empirical pathloss models

Empirical pathloss models estimate transmission losses not based on theoretical expressions but relying entirely on direct measurements. They fully characterize a scenario but they are strictly dependent on the environment and hardware characteristics. The pathloss model adopted in this thesis has been obtained empirically by following the procedure described in [14][15] and explained below.

The target is to build a pathloss model which represents the signal decay caused by distance and obstructions among the path. With this purpose, MS is placed at several distances from 1m to 20m with respect to one AP (see Fig. 3.9), measuring the RSS level in each location. In order to mitigate the problem of high fluctuations on the signal strength, multiple measurements are collected in each position, storing the resulting average.

Real measured results of this site-survey for a single AP can be observed in Fig. 3.10. At this point, set of data must be converted into some pathloss model expression in

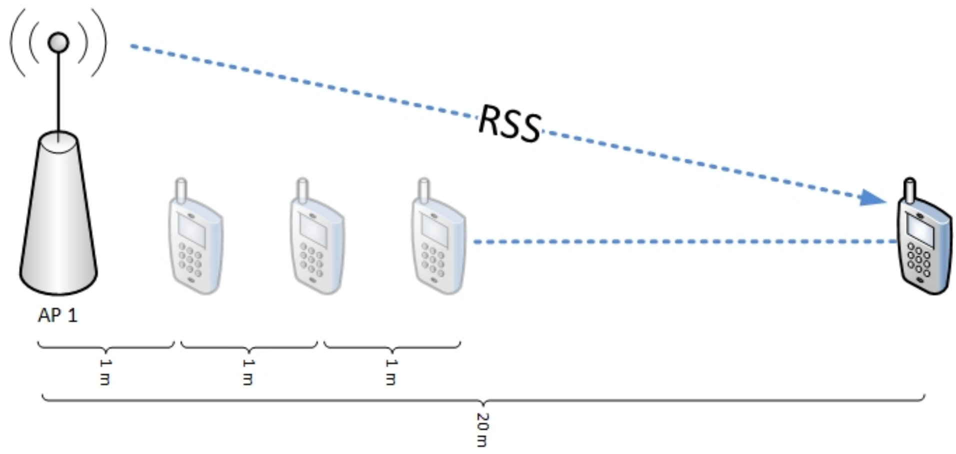

Figure 3.9 *Pathloss model definition*

order to be able to relate RSS levels (dBm) with distances (m). For that purpose, *regression analysis*, also known as *curve fitting*, is performed, with the target of constructing a mathematical function which best fits the series of experimental data.

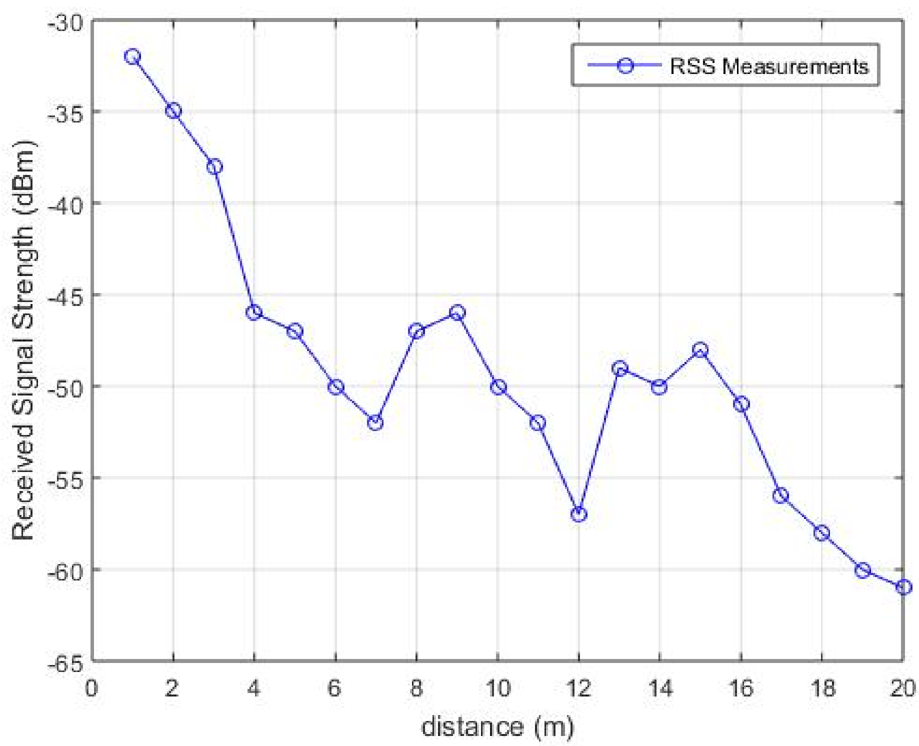

Figure 3.10 *Mean value of the RSS measurements at each step*

In this MSc thesis, *polynomial regression* is applied to construct the empirical pathloss model since polynomials are easily evaluated and are the best suited for interpolation [48]. Polynomial regression is a type of regression where relationship between independent variable x and dependent variable y is modeled as an nth degree polynomial:

$$y = a_0 + a_1 x + a_2 x^2 + a_3 x^3 + ... + a_n x^n \tag{3.2}$$

The goal in polynomial regression is to determine coefficients $a_0,\ a_1,\ a_2,\ a_3,\ ...,\ a_n$ that make the curve best fit the data points. Furthermore, there must be a trade-off when choosing the polynomial degree. A low degree will not provide enough accuracy when curve fitting whereas a high degree would suffer from over-fitting, adding severe complexity and computational overhead to the analysis.

Given the M training points $(d_m,\ RSS_m)$ collected from AP-MS in the area of interest, the ideal nth-degree polynomial should satisfy:

$$\hat{d_m} = a_0 + a_1 RSS_m + a_2 RSS_m^2 + a_3 RSS_m^3 + ... + a_n RSS_m^n \tag{3.3}$$

where $\hat{d_m}$ is the distance in meters between AP-MS, RSS_m is the received signal strength at MS and a_j $(j = 1, 2, ..., n)$ are the coefficients of the polynomial.

With the goal of calculating optimal polynomial degree, some experiments were conducted comparing the residuals among different degree polynomials applied to the experimental data, finally assuming that a 4th degree polynomial approximation would be adequate for the set of measurements collected:

$$\hat{d_m} = a_0 + a_1 RSS_m + a_2 RSS_m^2 + a_3 RSS_m^3 \tag{3.4}$$

In order to calculate the constants of the polynomial $a_0,\ a_1,\ a_2,\ a_3$, and, therefore, estimating the empirical pathloss model, *Least Squares* algorithm is applied.

Fig. 3.11 shows the set of previous collected data, together with the estimated empirical model using a 4th degree polynomial approximation.

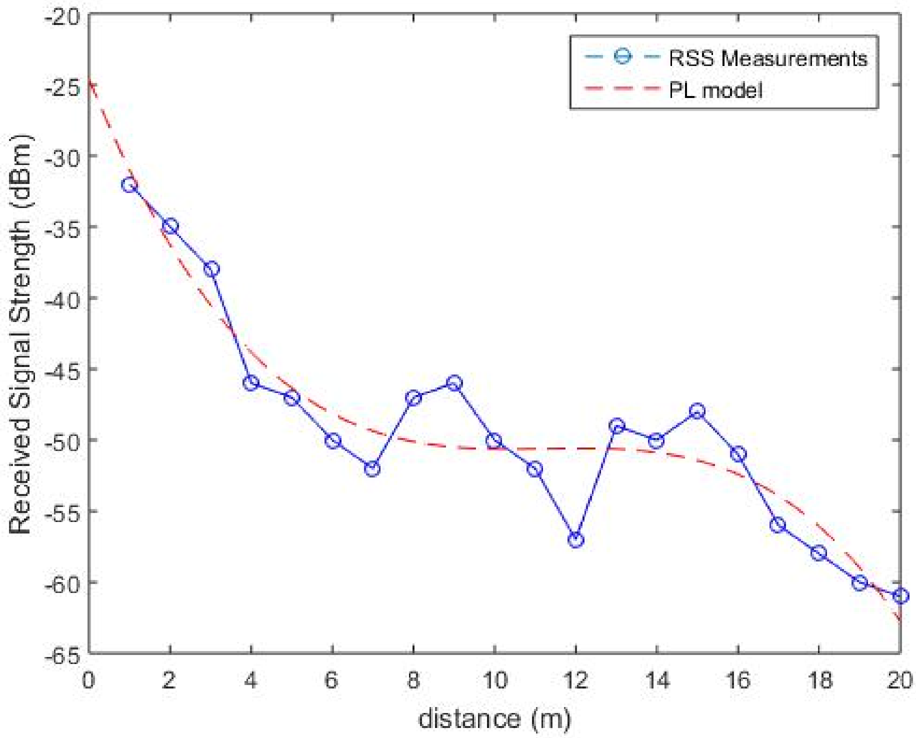

Figure 3.11 *Path loss calibration. Blue line represents the direct RSS measurements. Red line is the empirical pathloss model estimated by using 4th degree polynomial analysis.*

4. PATHLOSS-BASED POSITIONING ALGORITHMS

In this chapter, we will describe two proposed positioning algorithms based on pathloss models: *trilateration* and *Kalman Filtering*. They are applied in the online run-time stage, after several distances between APs and MS are estimated using the empirical pathloss model.

In *trilateration* technique, localization is performed by means of a *linearisation* procedure followed by *Least Squares* approximation, whereas in *Kalman filtering*, positioning is achieved by using a non-linear version of Kalman filter, called *Extended Kalman Filter*.

4.1 Trilateration

Trilateration is a technique widely used in surveying and navigation which provides the absolute position of a target as the intersection point among different circles. In order to get an unique solution, at least three or more circles must be defined (see Fig. 4.1).

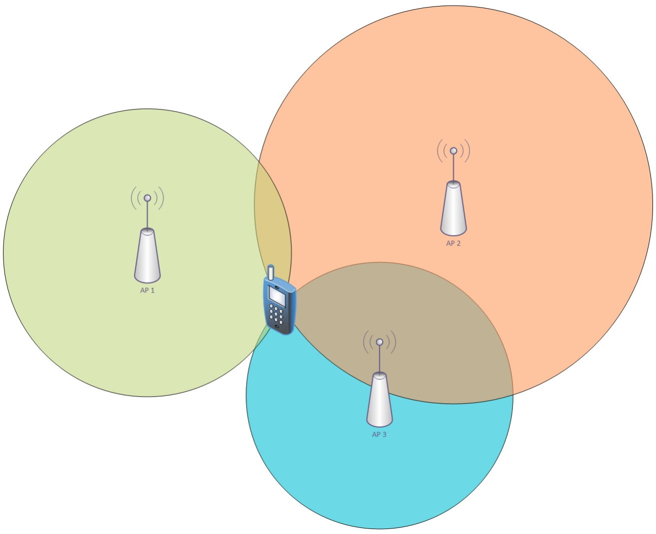

Figure 4.1 *Trilateration algorithm*

In our scenario, circles are formed by a *radius* the distance between an AP and the MS node and a center the known AP position in the map. Furthermore, trilateration is performed by using 4 different distances between 4 APs and the mobile station, as observed in Fig. 4.2.

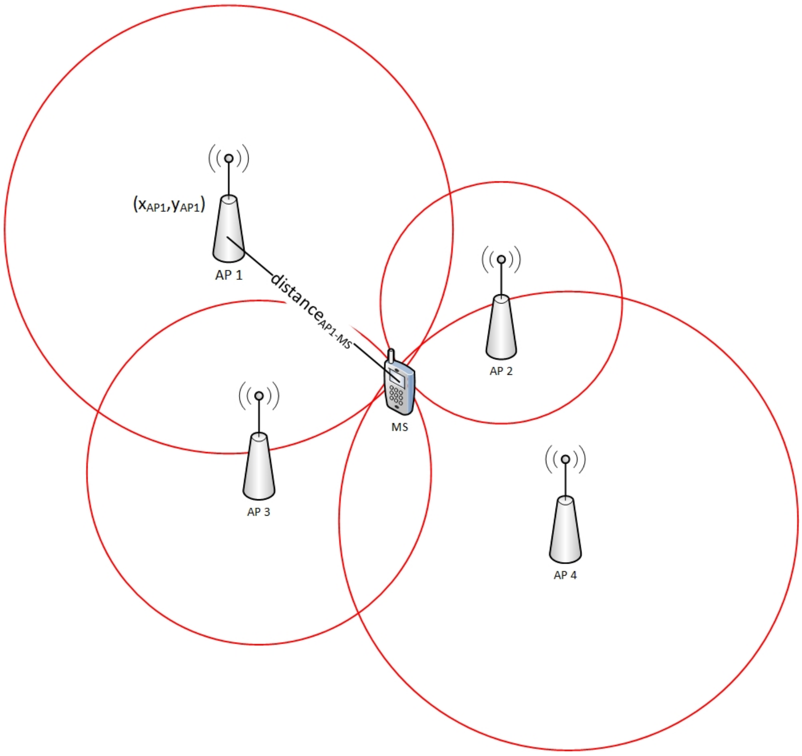

Figure 4.2 *Trilateration algorithm with four APs*

In order to find the intersection point, circles must be translated into equations that can be understood by computers. A 2-dimensional circle can be mathematically represented as

$$r_{AP-MS}^2 = (x_{MS} - x_{AP})^2 + (y_{MS} - y_{AP})^2 \tag{4.1}$$

where r_{AP-MS} is the range between Tx-Rx, in our case, the estimated distance between AP and MS, (x_{AP}, y_{AP}) are the known coordinates of the AP which form the center of the circle and (x_{MS}, y_{MS}) are the unknown coordinates of the mobile station, that lie in the circle circumference.

The four circles will be hence converted into four non-linear mathematical equations and intersection point will be found by solving the following system of equations:

$$
\begin{aligned}
r^2_{AP_1-MS} &= (x_{MS} - x_{AP_1})^2 + (y_{MS} - y_{AP_1})^2 \\
r^2_{AP_2-MS} &= (x_{MS} - x_{AP_2})^2 + (y_{MS} - y_{AP_2})^2 \\
r^2_{AP_3-MS} &= (x_{MS} - x_{AP_3})^2 + (y_{MS} - y_{AP_3})^2 \\
r^2_{AP_4-MS} &= (x_{MS} - x_{AP_4})^2 + (y_{MS} - y_{AP_4})^2
\end{aligned}
\tag{4.2}
$$

As it can be observed, there are two unknowns (x_{MS}, y_{MS}) and four equations so system is considered *overdetermined*. The positioning problem consists of finding the point (x_{MS}, y_{MS}) that simultaneously satisfies above equations. Intuitively, the position is calculated by solving the 4 equations simultaneously for (x_{MS}, y_{MS}). However, doing so results in a non-linear system which is not easily solved [27]. To simplify things, firstly, non-linear expressions must be linearised and then, an algorithm capable to solve overdetermined system of equations must be applied. This is the case of *least squares* method.

4.1.1 Linearisation of the problem

In summary, circular trilateration is performed to find the MS position. Circle equations are non-linear expressions that are not easy to handle. For this reason, a linearisation must be applied on the equations before performing Least Squares methods.

The main idea behind linearisation problem is to obtain a set of linear equations from the non-linear circle relationships via simple addition and subtraction operations.

In order to understand how linearisation works, lets reorganize system of equations in 4.2 into:

$$
r_i^2 = (x - x_i)^2 + (y - y_i)^2, \qquad (i = 1, 2, ..., n) \tag{4.3}
$$

where n is number of APs required for positioning.

Following the procedure described in [27][28], the equation set 4.3 is linearised by arbitrarily selecting the jth equation as a linearisation tool. By simultaneously adding and subtracting x_j and y_j in 4.3, we get:

$$
(x - x_i + x_j - x_j)^2 + (y - y_i + y_j - y_j)^2 = r_i^2, \quad (i = 1, 2, ..., j-1, j+1, ..., n) \tag{4.4}
$$

By multiplying and regrouping the terms, this can be written as:

$$\begin{aligned} &(x - x_j)(x_i - x_j) + (y - y_j)(y_i - y_j) \\ &= \frac{1}{2}[(x - x_j)^2 + (y - y_j)^2 - r_i^2 + (x_i - x_j)^2 + (y_i - y_j)^2] \\ &= \frac{1}{2}[r_j^2 - r_i^2 + d_{i,j}^2] = b_{ij} \end{aligned} \tag{4.5}$$

where

$$d_{i,j}^2 = (x_i - x_j)^2 + (y_i - y_j)^2 \tag{4.6}$$

represents distance between AP_i and AP_j. x_i, y_i, x_j, y_j and d_{ij} are known variables. Both r_i and r_j can be estimated by using the empirical pathloss model from calibration stage.

We arbitrary select AP_1 as the linearisation tool. Therefore, by choosing $j = 1$, equation set 4.5 results into $n - 1$ linear equations, given by:

$$\begin{aligned} &(x - x_1)(x_i - x_1) + (y - y_1)(y_i - y_1) \\ &= \frac{1}{2}[r_1^2 - r_i^2 + d_{i,1}^2] = b_{i1} \end{aligned} \tag{4.7}$$

Written in matrix form, it is equivalent to:

$$\boldsymbol{A}\vec{x} = \vec{b} \tag{4.8}$$

where

$$\boldsymbol{A} = \begin{pmatrix} x_2 - x_1 & y_2 - y_1 \\ x_3 - x_1 & y_3 - y_1 \\ \dots & \dots \\ x_n - x_1 & y_n - y_1 \end{pmatrix} \quad \vec{x} = \begin{pmatrix} x - x_1 \\ y - y_1 \end{pmatrix} \quad \vec{b} = \frac{1}{2}\begin{pmatrix} b_{2,1} \\ b_{3,1} \\ \dots \\ b_{n,1} \end{pmatrix}$$

At this point, linearisation has been completed since non-linear equations have disappeared. The system has $n - 1$ independent equations. Next target is to find n, i.e., the number of APs that will be used for trilateration.

If distances r_i did not contain errors, 3 APs would be enough to define the system of equations and hence, system would be only formed by two linear equations and two unknowns, being easily solved by:

$$\vec{x} = \boldsymbol{A}^{-1}\vec{b} \tag{4.9}$$

However, since distances r_i are imperfect and approximated, this solution is not accurate.

In order to get an improved solution to the system, more than 3 AP must be used, getting as result an overdetermined system of linear equations, where solution 4.9 cannot be straightforward applied. A method capable to handle overdetermined systems is the *least squares* approximation [27].

In this MSc thesis, two different *Linear Least Squares* methods have been proposed.

4.1.2 Least Squares

Least Squares (LS) is an approach to solve overdetermined or inexactly specified systems of equations in an approximated sense.

There are two types of least square algorithms depending on the procedure followed:

- *Iterative Descent Methods*: LS algorithms which follow an iterative process until it converges at some point.
- *Direct Methods*: non-iterative LS algorithms which provide a direct solution based on some assumptions or simplifications.

We have proposed direct Least Squares algorithms in this work to simplify the computation effort.

Furthermore, Least Squares methods can also be divided into *linear* LS and *non-linear* LS:

- *Linear LS methods*: LLS is the problem of solving overdetermined systems of linear equations. It is a suboptimal position technique which facilitates low-complexity position estimation [22].
- *Non-linear LS methods*: NLLS is the problem of solving overdetermined system of non-linear equations. It provides accurate solutions but suffers from high complexity.

In order to avoid computational complexity of the NLLS approach, and still get reasonable positioning accuracy, LLS methods have been proposed in this MSc thesis.

Linear Least Squares

Instead of solving the equation set in 4.9 exactly, LLS seeks to minimize the sum of the squares of the *residuals* [9]. Consequently, this algorithm will output the position that best fits all of the distance measurements by minimizing the sum of squares of errors.

Let the residual, the error in the approximated solution $\vec{x}$, be denoted by $\vec{\triangle}$:

$$\vec{\triangle} = \vec{b} - \boldsymbol{A}\vec{x} \tag{4.10}$$

The sum of squared errors (SSE) may then be written as [27][33]:

$$SSE = \vec{\triangle}^T \vec{\triangle} = (\vec{b} - \boldsymbol{A}\vec{x})^T (\vec{b} - \boldsymbol{A}\vec{x}) \tag{4.11}$$

Minimizing the sum:

$$\frac{\partial SSE}{\partial \vec{x}} = -\boldsymbol{A}^T\vec{b} + (\boldsymbol{A}^T\boldsymbol{A}) = 0 \tag{4.12}$$

Giving as result the *normal equations*:

$$(\boldsymbol{A}^T\boldsymbol{A})\vec{x} = \boldsymbol{A}^T\vec{b} \tag{4.13}$$

If $(\boldsymbol{A}^T\boldsymbol{A})$ is *non-singular*, this equation may be solved by:

$$\hat{x} = (\boldsymbol{A}^T\boldsymbol{A})^{-1}\boldsymbol{A}^T\vec{b} \tag{4.14}$$

where $\hat{x}$ is the least square estimator and solution to the positioning problem.

If $(\boldsymbol{A}^T\boldsymbol{A})$ is singular or close to singular, it can not be straightforward inverted and a pseudo-inversion must be calculated by *QR decomposition* [33]:

- QR decomposition is a decomposition of matrix $\boldsymbol{A}$ into the product $\boldsymbol{A} = \boldsymbol{QR}$ where $\boldsymbol{Q}$ is an orthogonal matrix and $\boldsymbol{R}$ is upper triangular matrix, transforming the *normal equations* in 4.13 into

$$\begin{gathered}(\boldsymbol{QR})^T\boldsymbol{QR}\vec{x} = (\boldsymbol{QR})^T\vec{b} \Rightarrow \boldsymbol{R}\vec{x} = \boldsymbol{Q}^T\vec{b} \Rightarrow \\ \Rightarrow \vec{x} = \boldsymbol{R}^{-1}\boldsymbol{Q}^T\vec{b}\end{gathered} \tag{4.15}$$

which is easily solve because $\boldsymbol{R}$ is non-singular.

Using an external Java matrix library called *Efficient Java Matrix Library* (EJML) in this work has allowed to handle these operations without adding extra complexity. If $(\boldsymbol{A}^T\boldsymbol{A})$ is non-singular, EJML will return an unique solution as given by equation 4.14. Otherwise, EJML will return an exception which will be handled by performing QR decomposition.

Weighted Linear Least Squares

Ordinary least squares method assumes that there is constant variance in the distance errors [40], meaning that, LLS gives the same weight to different distance estimations. However, in our scenario, radii measurements are subject to errors. It is expected that the amount of error will be proportional to radii themselves. Hence, the accuracy of the distance estimations depends on the distance itself [50]. This can be observed in Fig. 4.3, where radius 3 is more informative than radius 1 and radius 2, hence it should get higher priority.

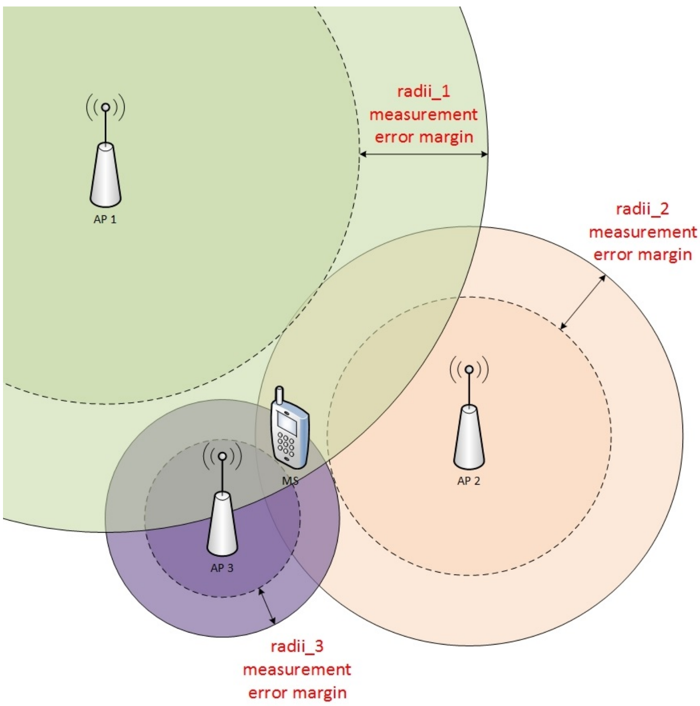

Figure 4.3 *Radii measurements scenario*

As a consequence, when greater weights are given to more accurate measurements, i.e., shorter distances, localization estimation will provide more accurate positioning solutions [50]. This approach is called *weighted least squares*. "When it may not be reasonable to assume that every observation should be treated equally, weighted least squares can often be used to maximize the efficiency of parameter estimation" [5].

The linear set of equations in 4.8 can be solved by applying a weighted linear least square estimator, as proposed in [50]

$$\hat{x} = (\boldsymbol{A}^T \boldsymbol{W} \boldsymbol{A})^{-1} \boldsymbol{A}^T \boldsymbol{W} \vec{b} \tag{4.16}$$

where $\boldsymbol{W}$ represents the weighted matrix and it is a *diagonal* matrix with weights inversely proportional to the squared radii:

$$\boldsymbol{W} = \begin{pmatrix} \frac{1}{\sqrt{d_1}} & 0 & 0 \\ 0 & \frac{1}{\sqrt{d_2}} & 0 \\ \dots & \dots & \vdots \\ 0 & 0 & \frac{1}{\sqrt{d_n}} \end{pmatrix} \tag{4.17}$$

4.2 Kalman Filtering

In this section, Kalman filtering theory will be introduced. In next chapter, when our system is fully characterized and described, Kalman filter design will be presented, carefully modeling the filter to our system conditions.

In short, a *Kalman Filter* (KF) [24][31][36] is a recursive algorithm which estimates the future state of a linear dynamic system based on noisy measurements and previous states. Thus, there are two models to define in order to apply a Kalman filter: *state model* and *measurement model*.

The *state* or *process* model is a dynamic model which describes how the system evolves over time. It must follow the physic laws of motion and it linearly relates the previous state of a system with the new one. The *space state* refers to a vector of n variables which represents some interesting properties of the system. The process model equation for Kalman filter is given as follows:

$$\boldsymbol{x}_k = \boldsymbol{F}_k \boldsymbol{x}_{k-1} + \boldsymbol{B}_k \boldsymbol{u}_k + \boldsymbol{w}_k, \qquad \boldsymbol{w}_k \sim \mathcal{N}(0, \boldsymbol{Q}_k) \tag{4.18}$$

where $\boldsymbol{x}_k$ is the current state of the system at time k, $\boldsymbol{F}_k$ refers to the state transition matrix which is applied to the previous state $\boldsymbol{x}_{k-1}$, $\boldsymbol{B}_k$ is the control-input model which is applied to the control vector $\boldsymbol{u}_k$ and $\boldsymbol{w}_k$ is the process noise, which is assumed to be zero mean white Gaussian noise with covariance $\boldsymbol{Q}_k$.

The *measurement model* or *observation model* relates linearly the current state with measurements corrupted by noise [39]. The measurement model equation is given by

$$\boldsymbol{z}_k = \boldsymbol{H}_k \boldsymbol{x}_k + \boldsymbol{v}_k, \qquad \boldsymbol{v}_k \sim \mathcal{N}(0, \boldsymbol{R}_k) \tag{4.19}$$

where $\boldsymbol{z}_k$ is the observation (or measurement) at time k, $\boldsymbol{H}_k$ is the observation matrix which maps linearly the true state space into the observed space and $\boldsymbol{v}_k$ is the measurement noise, which is assumed to be zero mean white Gaussian noise with covariance $\boldsymbol{R}_k$.

The process noise and measurement noise are statistically independent.

As previously mentioned, Kalman filter estimates the state of a system. However, in most practical cases, true state $\boldsymbol{x}_k$ cannot be directly observed so the Kalman filter provides an algorithm to determine an estimate $\hat{\boldsymbol{x}}_k$ by combining system and noisy measurement models. Kalman filter works with Gaussian distributions. Therefore, the estimates of the parameters of interest in the state vector are provided by *probability density functions* rather than discrete values [17].

Gaussian distributions are fully described by their mean and variance. Hence, state of the filter is represented by two key parameters:

$\hat{\boldsymbol{x}}_{k|k}$, the *a posteriori* state estimate at step k given measurement $\boldsymbol{z}_k$.

$\boldsymbol{P}_{k|k}$, the *a posteriori* error covariance matrix, which measures how accurate is the state estimate $\hat{\boldsymbol{x}}_{k|k}$

Kalman filter algorithm is divided into two different steps: *prediction step* and *update step*. At prediction step, KF uses the previous state information and physic laws of motion in order to predict the current estimate of state variables. At update step, current observation is used to correct the estimate done at prediction step [30]. The algorithm at step k has the following form:

Time update (prediction)	
Predicted (*a priori*) state	$\hat{\boldsymbol{x}}_{k\|k-1} = \boldsymbol{F}_k \hat{\boldsymbol{x}}_{k-1\|k-1} + \boldsymbol{B}_k \boldsymbol{u}_k$
Predicted (*a priori*) estimate covariance	$\boldsymbol{P}_{k\|k-1} = \boldsymbol{F}_k \boldsymbol{P}_{k-1\|k-1} \boldsymbol{F}_k^T + \boldsymbol{Q}_k$
Measurement update (correction)	
Innovation	$\boldsymbol{y}_k = \boldsymbol{z}_k - \boldsymbol{H}_k \hat{\boldsymbol{x}}_{k\|k-1}$
Innovation covariance	$\boldsymbol{S}_k = \boldsymbol{H}_k \boldsymbol{P}_{k\|k-1} \boldsymbol{H}_k^T + \boldsymbol{R}_k$
Kalman gain	$\boldsymbol{K}_k = \boldsymbol{P}_{k\|k-1} \boldsymbol{H}_k^T \boldsymbol{S}_k^{-1}$
Updated (*a posteriori*) state	$\hat{\boldsymbol{x}}_{k\|k} = \hat{\boldsymbol{x}}_{k\|k-1} + \boldsymbol{K}_k \boldsymbol{y}_k$
Updated (*a posteriori*) estimate covariance	$\boldsymbol{P}_{k\|k} = (\boldsymbol{I} - \boldsymbol{K}_k \boldsymbol{H}_k) \boldsymbol{P}_{k\|k-1}$

At time update, filter predicts the *a priori* state estimate by using the linear state model, i.e., KF predicts where system is going to be. It also estimates the *a priori* covariance matrix which is a measurement of how much error the predicted state contains.

At measurement update, filter firstly gets the residual between the real observation and the predicted observation, defined as $\boldsymbol{y}_k$. As well as previous step, it also computes the innovation covariance which tells how much the innovation can be trusted. *Kalman gain* is the blending factor of the algorithm since it says to the filter how much it should change the predicted estimate by given a measurement. After calculating Kalman gain, the updated state is computed, together with its covariance, which informs how much error contains the *a posteriori* state $\hat{\boldsymbol{x}}_{k|k}$. In summary, in this step filter gets feedback in form of noisy measurements to refine the *a posteriori* state estimate.

All measurements in real applications suffer from noise and must be estimated in some degree. As observed, the Kalman Filter computes a *weighted mean* between the prediction of a system's state and the current observation. While trilateration technique estimated the position only based on measurements, the Kalman Filter combines both: measurements with states. The weights are calculated from the covariances, which define how much error the models contain. Therefore, values with higher certainty will be "trusted" more by the filter, affecting the final result more than values which are not so certain. The result of the weighted average is a new state estimate that lies between the predicted and measured state, and has a lower estimated uncertainty than either alone [16].

Kalman filtering works under two assumptions:

- Process and measurement noises are white and Gaussian.
- Motion and observation models are linear functions.

However, most realistic problems in navigation involve non-linear functions. As observed in previous section 4.1, distance measurements are converted into circle equations, which are non-linear relationships. Therefore, Kalman Filter is not applicable in our scenario.

4.2.1 Extended Kalman Filter

Extended Kalman Filter (EKF) is a non-linear version of Kalman filtering which solves the problem of linear Kalman filters. In EKF, state and observation equations are non-linear difference equations:

$$\begin{aligned} \boldsymbol{x}_k &= f(\boldsymbol{x}_{k-1}, \boldsymbol{u}_k) + \boldsymbol{w}_k, \qquad \boldsymbol{w}_k \sim \mathcal{N}(0, \boldsymbol{Q}_k) \\ \boldsymbol{z}_k &= h(\boldsymbol{x}_k) + \boldsymbol{v}_k, \qquad \boldsymbol{v}_k \sim \mathcal{N}(0, \boldsymbol{R}_k) \end{aligned} \tag{4.20}$$

where f is a non-linear function which computes the predicted state at time k from the previous state and similarly function h links the predicted measurement at time k with the predicted state at time $k-1$.

The core of EKF algorithm is the linearization of the motion and measurement models by using a *first order Taylor's approximation.* Difference equations in 4.20 become into:

$$\boldsymbol{x}_k \approx f(\hat{\boldsymbol{x}}_{k-1}, \boldsymbol{u}_k) + \boldsymbol{F}_{k-1}(\boldsymbol{x}_{k-1} - \hat{\boldsymbol{x}}_{k-1}) + \boldsymbol{w}_{k-1} \qquad \boldsymbol{w}_{k-1} \sim \mathcal{N}(0, \boldsymbol{Q}_{k-1}) \tag{4.21}$$

$$\boldsymbol{z}_k \approx h(\hat{\boldsymbol{x}}_k) + \boldsymbol{H}_k(\boldsymbol{x}_{k-1} - \hat{\boldsymbol{x}}_{k-1}) + \boldsymbol{v}_{k-1} \qquad \boldsymbol{v}_{k-1} \sim \mathcal{N}(0, \boldsymbol{R}_{k-1}) \tag{4.22}$$

where f is evaluated at the linearization point, which is the best local approximation of the function, i.e., the best known estimate $\hat{\boldsymbol{x}}_{k-1}$. $\boldsymbol{F}$ is the *Jacobian* matrix of function f. Furthermore, $\boldsymbol{F}$ is multiplied by $(\boldsymbol{x}_{k-1} - \hat{\boldsymbol{x}}_{k-1})$, which compares how far away previous state is from the linearization point. For measurement model, non-linear function h is also evaluated at the best known estimated state and $\boldsymbol{H}$ represents the Jacobian of h.

Jacobian matrix is the matrix which computes all the first-order partial derivatives of a vector-valued function. Given $f(x)$, a vector-valued function

$$\boldsymbol{f}(x) = \begin{pmatrix} f_1(x) \\ f_2(x) \\ \dots \\ f_m(x) \end{pmatrix}$$

Jacobian matrix is defined as

$$\boldsymbol{F}_{mxn} = \frac{\partial \boldsymbol{f}_m}{\partial \boldsymbol{x}_n} = \begin{pmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \dots & \frac{\partial f_1}{\partial x_n} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \dots & \frac{\partial f_2}{\partial x_n} \\ \dots & \dots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1} & \frac{\partial f_m}{\partial x_2} & \dots & \frac{\partial f_m}{\partial x_n} \end{pmatrix}$$

As with the original Kalman Filter, the Extended Kalman Filter uses a two-step predictor-corrector algorithm given by:

$$\begin{aligned} &\textbf{Time update (prediction)} \\ \text{Predicted state} \quad & \hat{\boldsymbol{x}}_{k|k-1} = f(\hat{\boldsymbol{x}}_{k-1|k-1}, \boldsymbol{u}_{k-1}) \\ \text{Predicted estimate covariance} \quad & \boldsymbol{P}_{k|k-1} = \boldsymbol{F}_{k-1}\boldsymbol{P}_{k-1|k-1}\boldsymbol{F}_{k-1}^{T} + \boldsymbol{Q}_{k-1} \end{aligned}$$

$$\begin{aligned} &\textbf{Measurement update (correction)} \\ \text{Innovation} \quad & \boldsymbol{y}_k = \boldsymbol{z}_k - h(\hat{\boldsymbol{x}}_{k|k-1}) \\ \text{Innovation covariance} \quad & \boldsymbol{S}_k = \boldsymbol{H}_k\boldsymbol{P}_{k|k-1}\boldsymbol{H}_k^{T} + \boldsymbol{R}_k \\ \text{Kalman gain} \quad & \boldsymbol{K}_k = \boldsymbol{P}_{k|k-1}\boldsymbol{H}_k^{T}\boldsymbol{S}_k^{-1} \\ \text{Updated } (\textit{a posteriori}) \text{ state} \quad & \hat{\boldsymbol{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{K}_k\boldsymbol{y}_k \\ \text{Updated } (\textit{a posteriori}) \text{ estimate covariance} \quad & \boldsymbol{P}_{k|k} = (\boldsymbol{I} - \boldsymbol{K}_k\boldsymbol{H}_k)\boldsymbol{P}_{k|k-1} \end{aligned}$$

Due to the non-linear properties of state transition and measurement models, f and h cannot be applied directly. Alternatively, EKF uses the Jacobians of these functions, which represent the linearization of the models.

Unlike its predecessor, the EKF is not an optimal estimator because it linearizes the process and observation models by applying an approximation. Furthermore, if models are defined inaccurately, EKF might diverge quickly, leading to really poor estimates. Moreover, definition of noise covariance matrices must be done precisely, otherwise large errors will lead EKF to fail. Having stated this, however, Extended Kalman filter, in practice, when is used carefully can give very good performance [23].

5. EXPERIMENTAL ACTIVITY

In this chapter, experimental activity is introduced, presenting the scenario where the experiment takes place, the devices used and a brief explanation of the system framework architecture. In the last section, the three indoor positioning approaches proposed in this MSc thesis are described in detail.

5.1 Scenario: Tietotalo's first floor indoor map

In order to test the different proposed approaches and evaluate their position accuracy, experiments have been carried out on first's floor of Tietotalo's building at Tampere University of Technology, focusing most part of them in the upper-left area, as illustrated in Fig. 5.1.

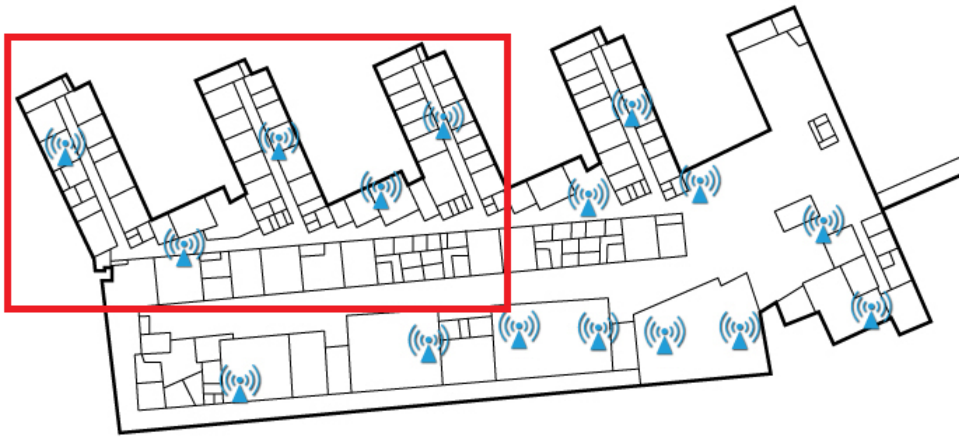

Figure 5.1 *First floor of Tietotalo's building. Red rectangle area refers to the place where most of experiments were conducted and Wi-Fi icons to the several AP distributed on the area*

5.2 Devices

5.2.1 Android mobile phone

An Android smartphone (Motorola Moto G 2014) with ongoing Wi-Fi capabilities have been used for collecting measurements as well as implementing, debugging and testing the different proposed approaches. Its operating system is Android 5.0 Lollipop. Thence, approaches have been developed in *Java* programming language, using *Android software development kit* (SDK) tools.

5.2.2 WLAN Access Points

WLAN infrastructure is already installed in the building. A total of 18 APs 802.11n Cisco are deployed within Tietotalo's first floor area, for providing Internet connectivity and data transfer.

In order to achieve indoor localization, it is a requirement for the mobile station to know *a priori* the several AP coordinates on the map and their respective MAC addresses. For that purpose, at the beginning of the MSc thesis, a series of experiments were conducted and a database containing pairs of data (AP coordinate - MAC address) was created and stored on the mobile phone:

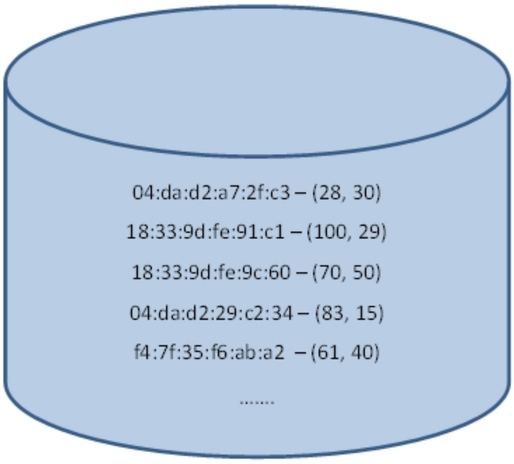

Figure 5.2 *The a priori database containing AP coordinates and MAC addresses.*

5.3 Software Framework Architecture

In this section the framework architecture which allows the Android mobile phone to perform positioning on the mentioned environment is briefly described from a software point of view. The main target of this software block is to make a decision about which localization approach the application should use at every scanning step, depending on the number of APs acquired. For that purpose, it firstly must collect and manipulate all the information coming from the available APs. It has been implemented following the MVC (*Model-View-Controller*) design pattern in an structured way. Fig. 5.3 shows a basic illustration of the whole system implementation.

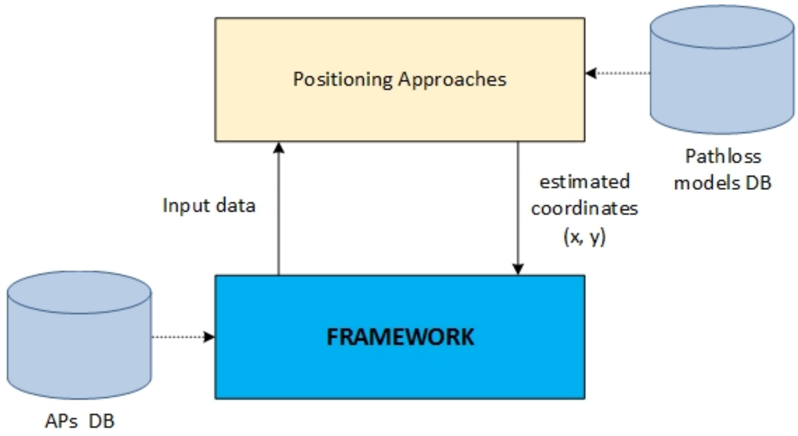

Figure 5.3 *Basic look of the whole system implementation*

It is a generic framework divided into well-defined modules which performs all the necessary tasks required to collect in real time the data which will be used by the different approaches proposed. Its main tasks are scanning available APs, filtering the unnecessary data out, making the decision and addressing the data to the different algorithms. Furthermore, when positioning techniques output the estimated MS coordinates, it also displays the coordinates on the map. The application flow can be seen in Fig. 5.4. These tasks, and how they have been implemented, will be briefly explained below.

In order to scan and gather the WLAN information from the mobile phone, we utilize two WiFi Android APIs: *WiFiManager* [4] and *ScanResult* [2]. The first one allows MS to listen for the APs beacons. The second one provides a way to handle in an efficient way all the information scanned from one AP: RSS levels, *BSSIDs*, *SSIDs*, frequency, timestamps, etc.

When the scanning process is finished, MS has gathered a lot of information from all the available APs. At this stage, it is required to filter all useless information out. Firstly, all the APs which are not in our AP database must be removed from the result list. TUT wireless network has 4 SSIDs for each AP, hence secondly only one SSID must be chosen from the list, filtering the rest out. Thirdly and last, from each scan result of each AP, needless data is removed, leaving only MAC addresses and signal strengths.

At next stage, the framework decides, based on the number of APs acquired, if the chosen technique will be AP-ID versus PL-based using trilateration or EKF.

When algorithms output the estimated MS coordinates, the map screen is updated and the whole cycle is repeated again. For displaying the first floor of Tietotalo's

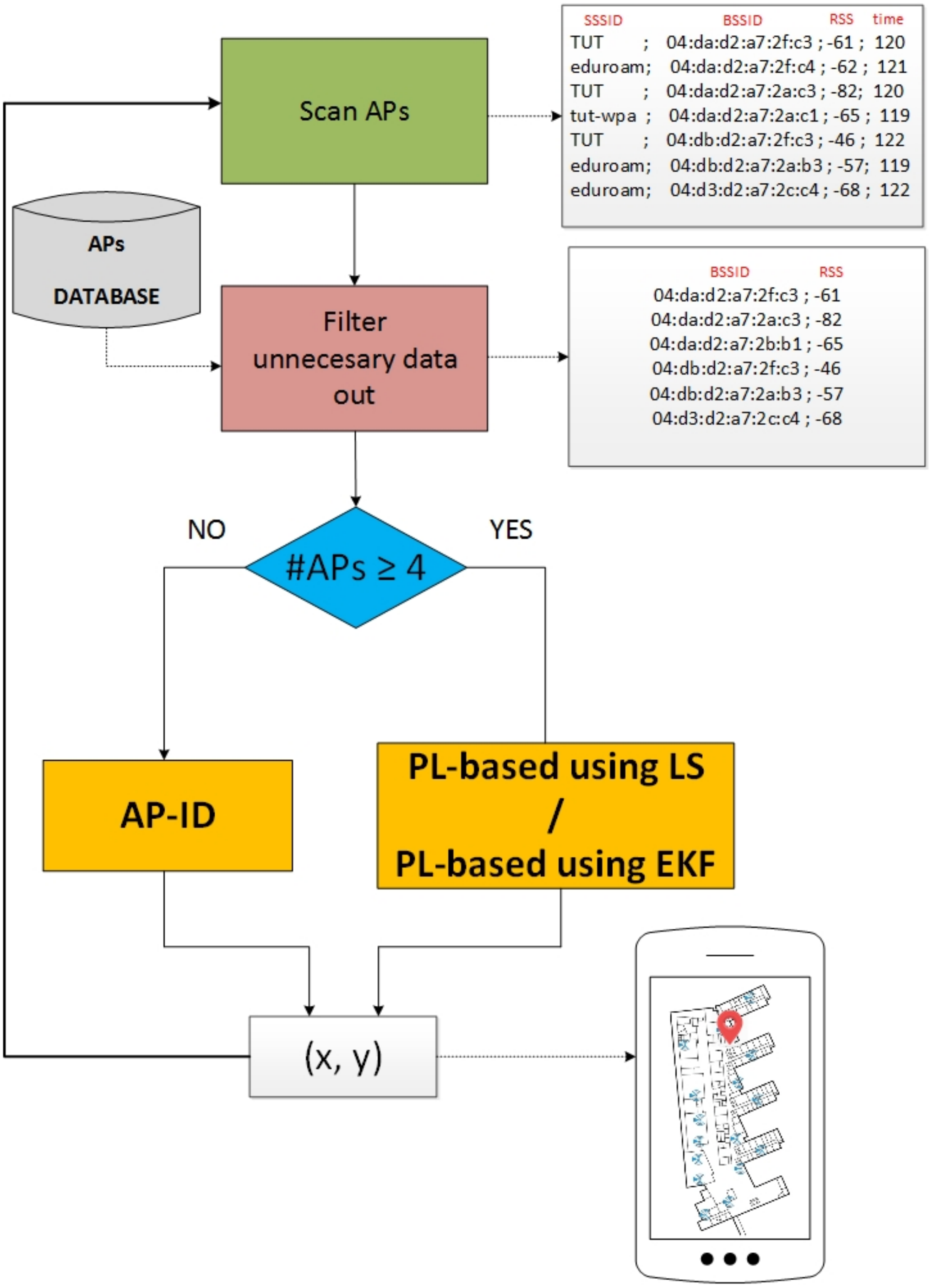

Figure 5.4 *Application flow*

map on the screen and providing basic functionalities such as dragging, flinging, pinch or double-tap to zoom, an external widget called *TileView* [3] is used.

In order to reduce complexity of the application and aiming to improve also performance, it is important to note that multiple threads have been used on the Android implementation. There are a total of three main threads which run concurrently: the *user interface* (UI) thread, which displays the map and allows user to manipulate it; the scanning thread, which is triggered every time that MS sweeps the channels; and the positioning algorithm thread, which performs the MS localization using one of the proposed approaches when scanning process is finished.

5.4 Approaches proposed

Once that the software framework of the application has been presented, we will focus at this section on the three localization approaches proposed on this MSc thesis.

5.4.1 AP-ID

As introduced on chapter 3.3.1, AP-Identifier is a proximity technique which estimates the location of a mobile station as the position of the AP with the strongest RSS level. Since it only provides coarse granularity accuracy, this method will be only used under the worst conditions: when there are not enough APs within the area to perform *PL-based using LS* or *PL-based using EKF* localization.

The application flow is illustrated in Fig. 5.5, which shows the easiness on implementing this technique.

5.4.2 Pathloss-based method using trilateration

When number of APs acquired is greater than three, it means that there will be at least four distance estimations and hence, *pathloss-based techniques* can be applied.

At this point, having reviewed all the previous literature, pathloss-based approach using trilateration can be fully characterized. It is a RSS-based indoor positioning technique which estimates the MS position by applying trilateration with the distance estimations from the empirical pathloss model built in the calibration stage. The flow of the approach at the online stage can be observed in Fig. 5.6, assuming that the empirical pathloss model has already been created at the calibration stage and stored into *PL model* database.

At first step after framework decision, entries of the scanning result list are sorted by the strongest RSS levels. If more than 4 APs are acquired, only the first four are chosen. Then, APs database is consulted and AP coordinates are paired to their respective MAC addresses and signal strengths. In the next module, the RSS

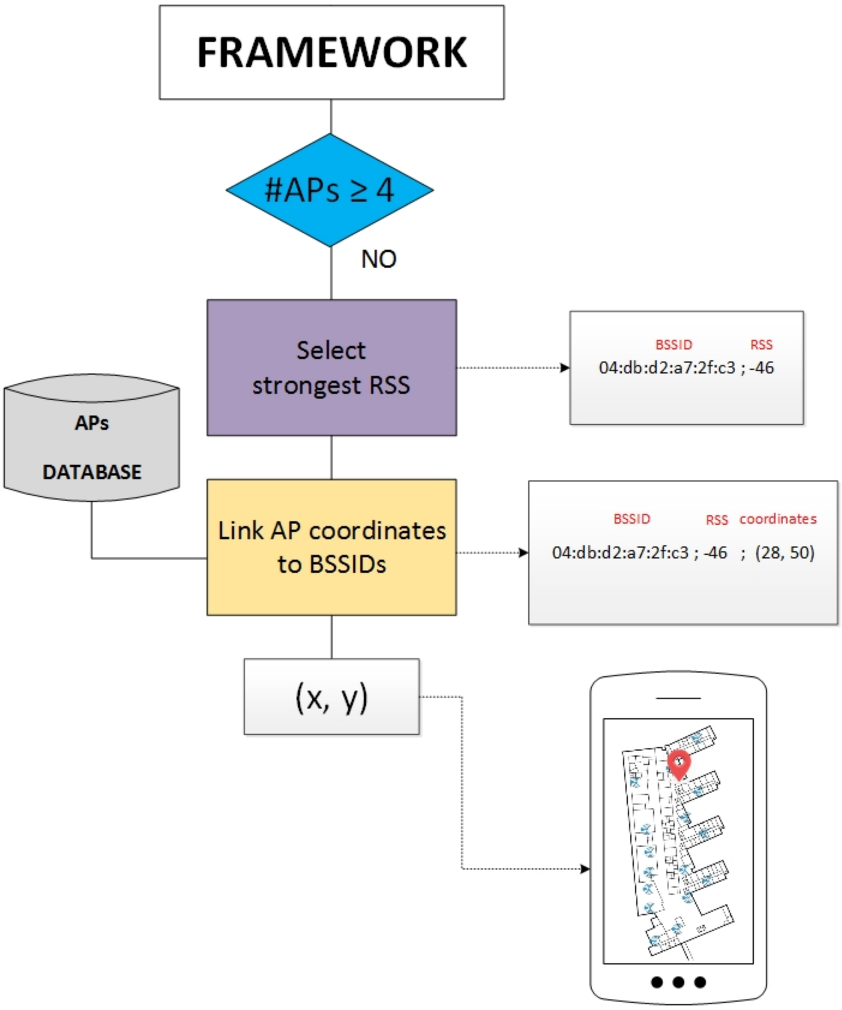

Figure 5.5 *AP-ID technique flow*

levels are translated into distances by consulting the empirical pathloss model from the database. Finally, trilateration is applied using Linear Weighted Least Squares algorithm, as thoroughly explained in section 4.1.

5.4.3 Pathloss-based method using Extended Kalman Filter

Pathloss-based technique using Extended Kalman Filter is a RSS-based method which estimates the MS location by computing a weighted mean between the system states and noisy distance measurements, which are translated from RSS levels by using the empirical pathloss model.

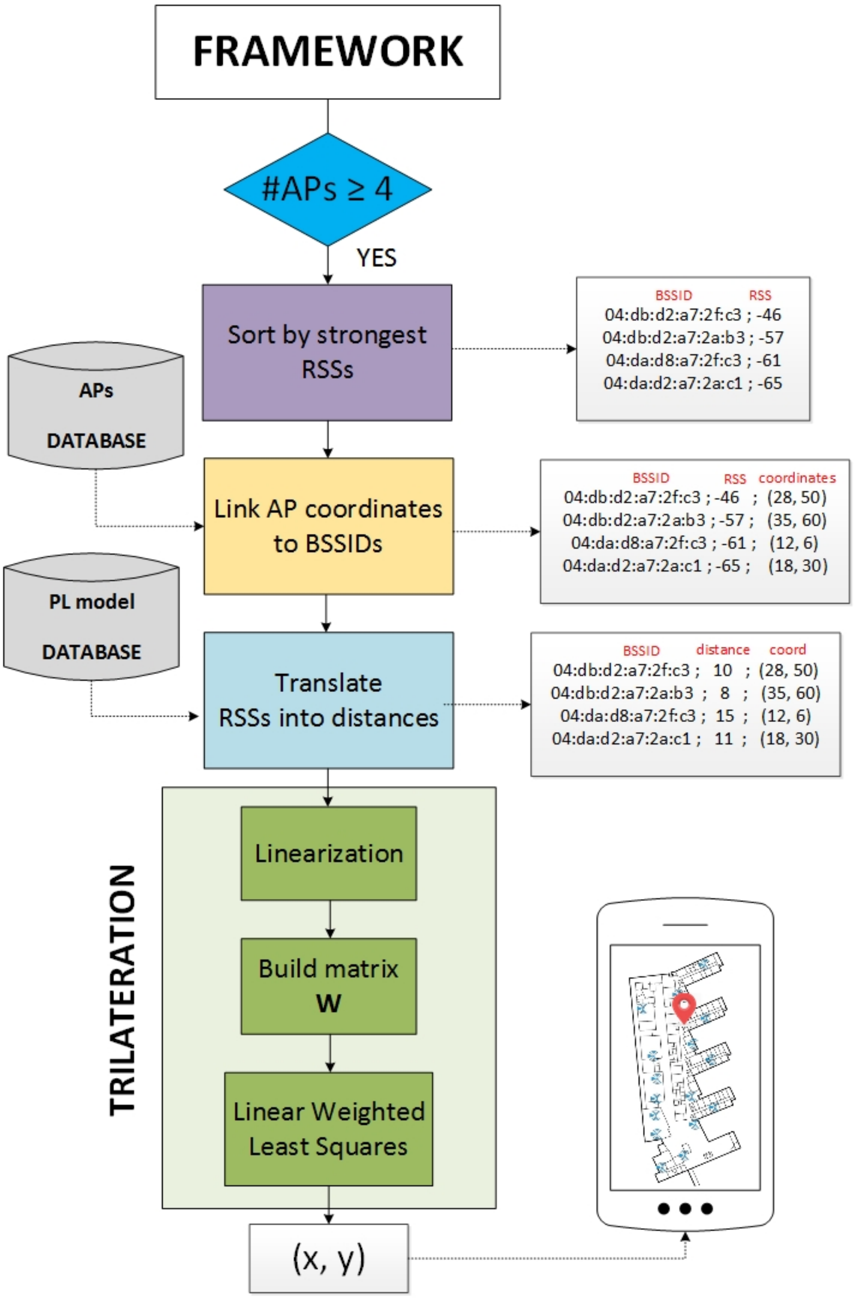

Figure 5.6 *PL-based technique using trilateration flow*

Filter design

In section 4.2.1, EKF was described from a theoretical point of view. At this moment, system has been fully characterized so Kalman filter parameters and models can finally be defined.

In this MSc thesis, we assumed no external excitation (control input $\boldsymbol{u}_k = 0$) and a static mobile station. The space state at iteration k is defined by the 2D coordinates of the mobile station given by:

$$\boldsymbol{x}_k = \{x_k^{MS} y_k^{MS}\} \tag{5.1}$$

and the state dynamic model is given by the following equation:

$$\boldsymbol{x}_k = \boldsymbol{F}_k \boldsymbol{x}_{k-1} + \boldsymbol{w}_k, \qquad \boldsymbol{w}_k \sim \mathcal{N}(0, \boldsymbol{Q}_k) \tag{5.2}$$

Since we have assumed static user, $\boldsymbol{F}_k = \boldsymbol{I}$. Noise covariance matrix $\boldsymbol{Q}$ specifies how much the actual motion of the model deviates from the assumed motion model. Because MS is fixed at the same position and it actually never moves, $\boldsymbol{Q}$ might be assumed to be zero, i.e., $\boldsymbol{Q} = \boldsymbol{0_{2x2}}$.

The measurement model which relates the current state (coordinates of the MS) with the measurements corrupted by noise (estimated distances) is given by the following expression:

$$\boldsymbol{z}_k = \boldsymbol{h}_d(\boldsymbol{x}_k) + \boldsymbol{v}_k, \qquad \boldsymbol{v}_k \sim \mathcal{N}(0, \boldsymbol{R}_k) \tag{5.3}$$

where the elements of the vector $\boldsymbol{h}_d$ are the distances between the MS and the four acquired APs, given by:

$$\boldsymbol{h}_d = \begin{pmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \end{pmatrix} = \begin{pmatrix} \sqrt{(x_{MS} - x_{AP_1})^2 + (y_{MS} - y_{AP_1})^2} \\ \sqrt{(x_{MS} - x_{AP_2})^2 + (y_{MS} - y_{AP_2})^2} \\ \sqrt{(x_{MS} - x_{AP_3})^2 + (y_{MS} - y_{AP_3})^2} \\ \sqrt{(x_{MS} - x_{AP_4})^2 + (y_{MS} - y_{AP_4})^2} \end{pmatrix} \tag{5.4}$$

In order to be used on the algorithm, non-linear vector-valued function $\boldsymbol{h}_d$ must be linearised by applying a first order's Taylor expansion:

$$\boldsymbol{z}_k \approx \boldsymbol{h}_d(\hat{\boldsymbol{x}}_k) + \boldsymbol{H}_k(\boldsymbol{x}_{k-1} - \hat{\boldsymbol{x}}_{k-1}) + \boldsymbol{v}_{k-1} \qquad \boldsymbol{v}_{k-1} \sim \mathcal{N}(0, \boldsymbol{R}_{k-1}) \tag{5.5}$$

where $\boldsymbol{H}_k$ is the Jacobian of $\boldsymbol{h}_d$ and it is computed as follows:

$$\boldsymbol{H}_k = \left[\frac{\partial \boldsymbol{h}_i}{\partial \boldsymbol{x}}\right]_{\boldsymbol{x}=\hat{\boldsymbol{x}}} = \begin{bmatrix} \frac{\hat{x}-x_{AP_1}}{h_1(\hat{\boldsymbol{x}}_k)} & \frac{\hat{y}-y_{AP_1}}{h_1(\hat{\boldsymbol{x}}_k)} \\ \frac{\hat{x}-x_{AP_2}}{h_2(\hat{\boldsymbol{x}}_k)} & \frac{\hat{y}-y_{AP_2}}{h_2(\hat{\boldsymbol{x}}_k)} \\ \frac{\hat{x}-x_{AP_3}}{h_3(\hat{\boldsymbol{x}}_k)} & \frac{\hat{y}-y_{AP_3}}{h_3(\hat{\boldsymbol{x}}_k)} \\ \frac{\hat{x}-x_{AP_4}}{h_1(\hat{\boldsymbol{x}}_k)} & \frac{\hat{y}-y_{AP_4}}{h_4(\hat{\boldsymbol{x}}_k)} \end{bmatrix} \tag{5.6}$$

Next step is the determination of the measurement noise covariance $\boldsymbol{R}$. It expresses how accurate are the sensors that collect the noisy measurements. Hence, this covariance matrix can be seen as a quality factor and can be estimated from real measurements. Matrix $\boldsymbol{R}$ is given by:

$$\boldsymbol{R} = diag(\sigma_i) \qquad (i = 1, 2, ..., n) \tag{5.7}$$

where n is number of APs acquired.

In this work, $\boldsymbol{R}$ values have been determined experimentally from the available measurements of the indoor scenario.

At this point, every KF parameter and model have already defined. Therefore, taking all these facts into consideration, EKF algorithm turns into:

Time update (prediction)

Predicted state	$\hat{\boldsymbol{x}}_{k\|k-1} = \hat{\boldsymbol{x}}_{k-1\|k-1}$
Predicted estimate covariance	$\boldsymbol{P}_{k\|k-1} = \boldsymbol{P}_{k-1\|k-1}$

Measurement update (correction)

Innovation	$\boldsymbol{y}_k = \boldsymbol{z}_k - h(\hat{\boldsymbol{x}}_{k\|k-1})$
Innovation covariance	$\boldsymbol{S}_k = \boldsymbol{H}_k \boldsymbol{P}_{k\|k-1} \boldsymbol{H}_k^T + \boldsymbol{R}_k$
Kalman gain	$\boldsymbol{K}_k = \boldsymbol{P}_{k\|k-1} \boldsymbol{H}_k^T \boldsymbol{S}_k^{-1}$
Updated (*a posteriori*) state	$\hat{\boldsymbol{x}}_{k\|k} = \hat{\boldsymbol{x}}_{k\|k-1} + \boldsymbol{K}_k \boldsymbol{y}_k$
Updated (*a posteriori*) estimate covariance	$\boldsymbol{P}_{k\|k} = (\boldsymbol{I} - \boldsymbol{K}_k \boldsymbol{H}_k) \boldsymbol{P}_{k\|k-1}$

The filter is initialized by setting $\hat{\boldsymbol{x}}_{0|0}$ and $\boldsymbol{P}_{0|0}$ to constant values. $\boldsymbol{P}_{0|0}$ is a measurement of the estimated accuracy of the state estimate $\hat{\boldsymbol{x}}_{0|0}$. It indicates how much uncertainty there is in the state estimation. Therefore, as we cannot know the exact position of MS at first iteration, $\boldsymbol{P}_{0|0}$ should be initialized with a large value so it will specify to EKF that there is a large uncertainty about state estimate and filter should give priority to noisy measurements over predictions:

$$\boldsymbol{P}_{0|0} = \begin{bmatrix} L & 0 \\ 0 & L \end{bmatrix} \tag{5.8}$$

where L is a large value.

The initial guess position $\hat{\boldsymbol{x}}_{0|0}$ must be also defined as one of the inputs of the algorithm. In order to allow a faster convergence of the filter, the initial guess is computed as the estimate obtained from the trilateration technique using least square method.

Finally, the pathloss-based technique using EKF flow for one iteration is presented in Fig. 5.7

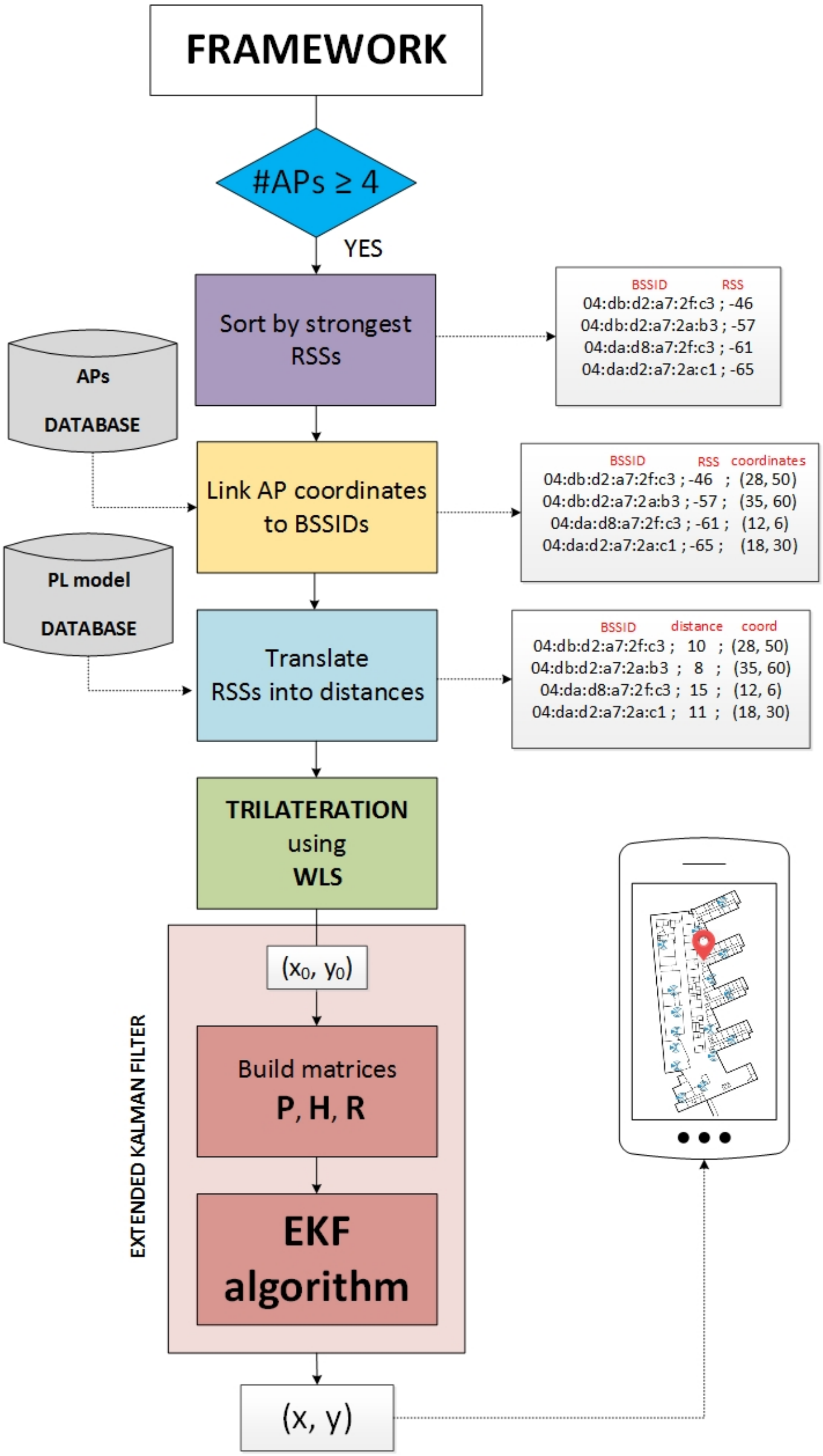

Figure 5.7 *PL-based technique using Extended Kalman Filter flow*

6. ANALYSIS OF RESULTS

In this chapter, we will present advantages and disadvantages of each technique previously proposed, observed from the experimental data collected. Furthermore, we evaluate the performance of these methods by calculating their *Residual Mean Standard Error* (RMSE). Finally, an analysis of the results is presented.

6.1 AP-ID

AP-ID proximity method provides a coarse accuracy positioning technique that can be used when indoor conditions are unfavorable and framework is not able to acquire more than 3 APs. Despite its coarse granularity precision, AP-ID is a technique easy to deploy and develop, which can be supported by all mobile handsets.

6.2 PL-based method using trilateration

Proposed pathloss-based method using trilateration provides an unique positioning solution, rather than approximately, as the previously mentioned technique. It entirely relies on noisy distance measurements, which are translated using an empirical pathloss model from time-varying RSS values. Therefore, there must be expected a loss in accuracy on the procedure, even before applying least squares algorithms. Furthermore, a linearisation on the circle equations must be made in order to perform linear least squares, which adds more uncertainty to the model. Nevertheless, PL-based using trilateration still provides easiness on its implementation since it only involves a few and simple small-matrix operations.

6.3 PL-based method using EKF

Pathloss-based using EKF technique uses distance measurements to perform localization, which are also converted by following the same procedure than previous technique. Nonetheless, it relies not only on the samples captured by the mobile station but also into the states of the system, therefore providing more accurate solution if, and only if, inputs of the filter are well defined and tuned for the scenario conditions. Furthermore, it is not always possible to properly define the process model of the system, leading the filter to diverge. Computational complexity of EKF is higher in comparison with least squares method, but still relatively low when compared with other filters. In summary, PL-based method using EKF provides accurate positioning with still relatively low complexity, when models are well defined and covariance matrices properly tuned to the scenario conditions.

In the following graph, we can observe a comparison of the previously mentioned techniques, in terms of complexity versus accuracy:

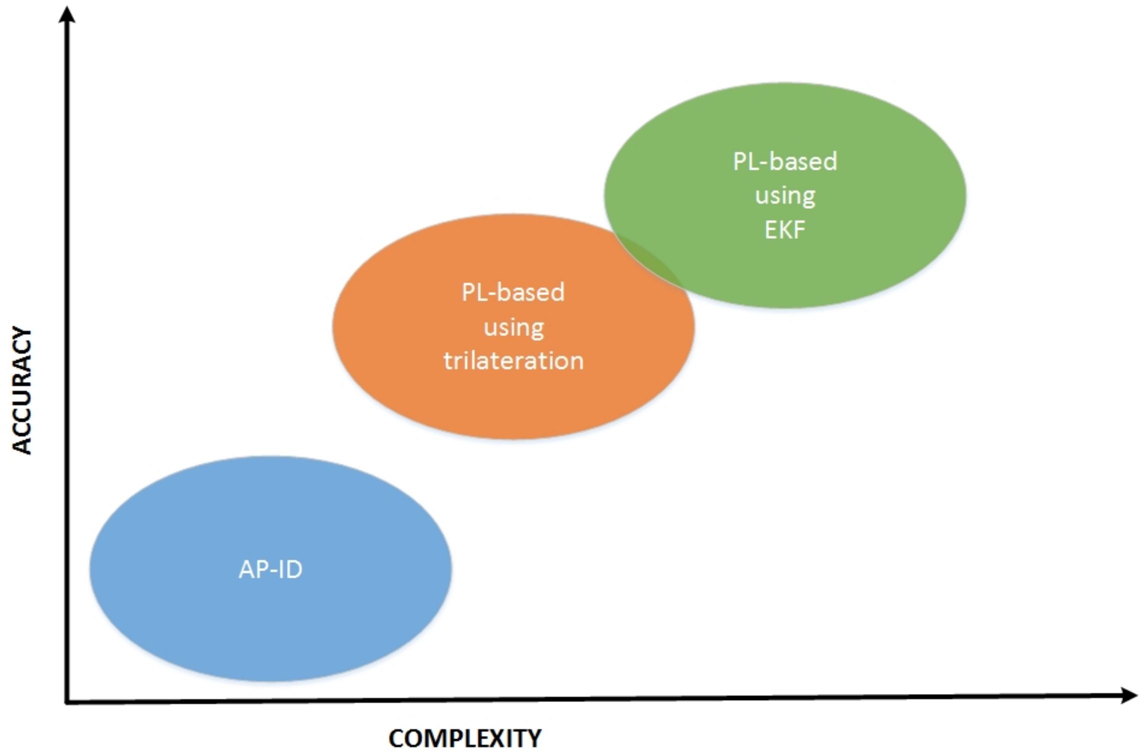

Figure 6.1 *Comparison graph of AP-ID, PL-based using trilateration and PL-based using EKF techniques.*

6.4 Root Mean Squared Error (RMSE) calculation

The performance of the proposed techniques is evaluated by quantifying the Root Mean Squared Error (RMSE), which calculates the difference between the real and estimated MS coordinates. In order to develop a RMSE for a set of n positions:

- Calculate the error, noted as ϵ, between each true MS location and the estimated one:

$$\epsilon_n = \sqrt{(x_{real,n} - x_{est,n})^2 + (y_{real,n} - y_{est,n})^2} \tag{6.1}$$

- RMS error is calculated by obtaining the square root of the average of the error ϵ:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(\epsilon_t)^2}{n}} \tag{6.2}$$

We analyzed the performance of the positioning techniques by computing the RMSE of each one for 100 measurements:

Table 6.1 *RMSE of proposed approaches.*

Proposed techniques	RMSE
AP-ID	15.82 m
PL-based using trilateration	7.10 m
PL-based using EKF	4.95 m

Table 6.1 shows the RMSE of the estimated positions for AP-ID, trilateration and EKF case. Gain improvement from AP-id to trilateration is 55 % (from 15.82 meters to 7.10 meters), whereas there is a 68 % improvement from AP-ID to EKF (from 15.82 meters to 4.95 meters). Finally, we observe than Kalman filter algorithm results in better performance than least square algorithm. Specifically, gain between PL-based using trilateration and PL-based using EKF is above 30 %. (from 7.10 meters to 4.95 meters)

6.5 Mapping of device location

Fig. 16 shows the map of the measurement area with the estimated positions of MS. The coordinates of the APs utilized in the experiment are as follows: AP1(28,29), AP2(40,46), AP3(61,39) and AP4(72,50); whereas MS exact position is (46, 32). Along with previous RMSE results, it might be observed how PL-based method using EKF gives better results in terms of accuracy with respect to trilateration method using least squares algorithm.

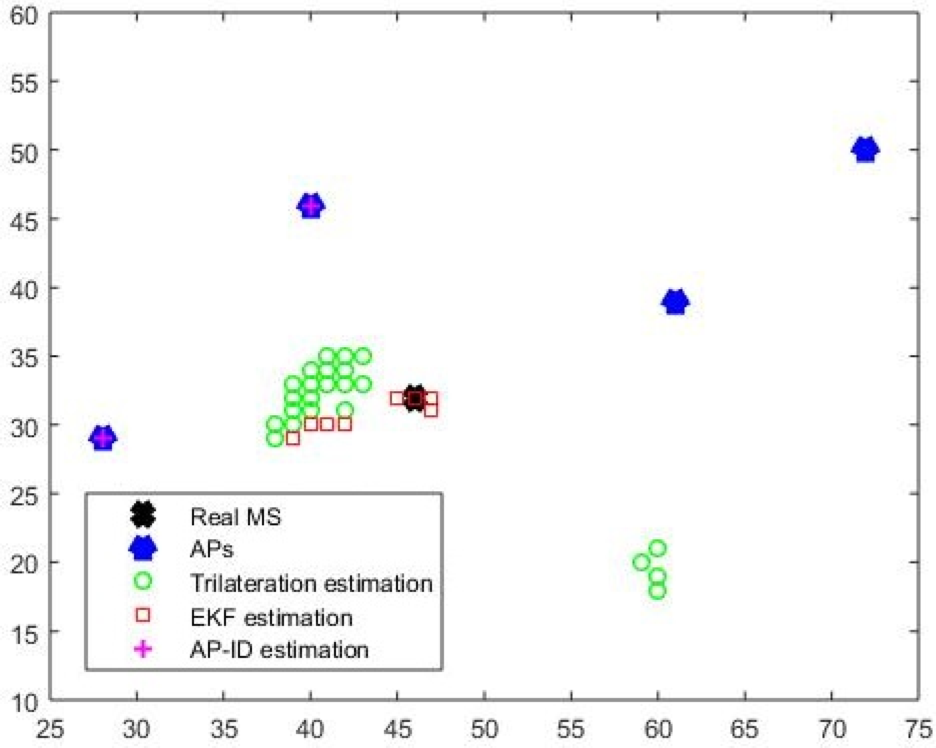

Figure 6.2 *Estimated positions with AP-ID, PL-based using trilateration and PL-based using EKF approaches.*

7. CONCLUSIONS AND FUTURE WORK

In this thesis, we have proposed several indoor positioning approaches to locate mobile devices within a WLAN network, by using the RSS measurements obtained from several APs. Furthermore, we have unified them into a single robust algorithm framework which always provides reasonable solutions, even under adverse conditions.

We have proposed the use of empirical pathloss models for the distance-based techniques in order to overcome the challenge of high fluctuations in RSS measurements, greatly dependent on the indoor environment. Polynomial regression analysis has been used to build a mathematical expression from the data. Several experiments have been conducted on various locations to study the behavior of different pathloss models from different access points when performing localization. A simple Android tool has been implemented to collect the data and construct the expression which best fits the samples.

To evaluate the performance of our approaches, we conducted different experiments in real locations inside Tietotalo's building within an already deployed Wireless LAN network. Results of the techniques show, in terms of RMSE, that AP-ID proximity approach, in comparison with the distance-based techniques, provides much poorer accuracy but higher robustness, since it always retrieves a solution, even with incomplete information. Results from the pathloss-based methods show accuracy, but there is still room for more improvement. This is mainly because of the high time-varying fluctuations of RSS levels in indoor scenarios.

7.1 Future work

An open future line of work which is being actually studied by the Department of Electronics and Communications Engineering in Tampere University of Technology is to deal with user's presence effects such as hand-grip, body loss and device orientation; which cause unpredictable behaviors into the RSS measurements, affecting the overall positioning system accuracy. By utilizing sensors embedded on the mobile phone as accelerometer, gyroscope and compass, we are able to predict user movements and therefore, mitigate and filter out the undesirable effects.

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